The relationship between skilled labor and technical change*

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Abstract

This study investigates whether capital-skill complementarity is the explanation for skill-biased technical change. For this to be the case, capital-skill complementarity must exist in the first place and, secondly, all technical change must be embodied in nature, i.e. embedded in new capital equipment. To test if these conditions are satisfied, a capital-age adjusted translog production function incorporating both embodied and disembodied technical change is implemented on a 14-industry panel for Swedish manufacturing 1985-95. The findings cast doubt on the claim that capital-skill complementarity can explain skill-biased technical change. In several industries, the capital-skill complementarity hypothesis is not supported. Moreover, it is found that the demand for skilled labor is affected by both disembodied and embodied technical change. An additional important result is that there is a negative skill-bias associated with embodied technical change.

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1. Introduction

During the last two decades, economists in many industrialized countries have faced the challenge of explaining the observation that the wage premium of skilled labor has increased despite considerable increases in the supply of this kind of workers. These changes provide evidence of considerable shifts in the relative demand for skilled workers. A number of explanations have been suggested in order to explain the latter.

Increased competition from low-wage countries in the Third World might have forced industrialized countries to concentrate on skill-intensive products and services, thus raising the demand for skilled workers; see, e.g., Wood (1994) and Feenstra and Hanson (1996). Or it may be that changes in firms' work organization have lead to increased skill requirements, cf. Caroli and van Reenen (2001), and Bresnahan, Brynjolfsson and Hitt (2002). However, the by far most popular explanation is the hypothesis of skill-biased technical change. This hypothesis says that technical change affects unskilled and skilled workers differently, favoring the latter, presumably because they have higher capacity for understanding and adopting new technologies. The idea was launched by Berman, Bound and Griliches (1994), and their analysis was followed up by a large number of studies [Machin and van Reenen (1998) provide an extensive survey on this issue]. The skill-biased technical change hypothesis has also been examined on Swedish data; see Hansson (1996) and Mellander (1999).

There are two problems with the skill-biased technical change hypothesis, however. The first relates to measurement: since there is no obvious way to measure technical change it is unclear how its presence should be tested. The second problem is that the skill-biased technical change hypothesis is not really an explanation – it merely raises another question, namely why technical change should affect workers with different skills unequally.

The measurement issue has spurred a lot of experimentation with different indicators of technical change in labor demand equations. A common procedure is to assume that technological change is exogenous to the firm and can be modeled by either the proportion of the workforce using computers [Autor, Katz and Kreuger (1998), Haskel and Heden (1999)] or expenditures on R & D [Berman, Bound and Griliches (1994)]. This approach is not very satisfactory, however. It is very hard to justify the exogeneity assumption: both computer capital and R&D expenditures are endogenous to the firm, just like the outlays on other factors of production.[1, 2]

The second problem with the skill-biased technical change hypothesis, i.e. that it lacks an explanation of why technical change affects skilled and unskilled workers differently, has been addressed by Krusell et al. (2000). They claim that, essentially, skill-biased technical change is just a reflection of capital-skill complementarity. The notion of capital-skill complementarity, due to Griliches (1969), predicts different relationships between capital, and skilled labor on the one hand and capital and unskilled labor, on the other hand. While capital tends to replace unskilled labor, implying that the two are substitutes, the demand for skilled tends to be positively affected by increases in capital, meaning that capital and skilled labor are complements. Krusell et al. (op.cit.) argue that the increased investments in high-tech capital equipment during the last decades, caused by falling relative prices of computers, have raised the ratio of effective capital inputs per worker and, thus, in particular per skilled worker. Skilled labor and capital being complements, this has lead to an increased demand for skilled workers.[3] However, to judge the validity of this explanation it is necessary to consider the mechanisms governing the diffusion of technical change.

Two forms of technical change are discussed in the literature: *embodied* and *disembodied* technical change. Embodied technical change is embedded in (new) capital goods. Computers are the most obvious example of capital goods featuring embodied technical change. Two PCs bought in different years will exhibit substantial differences in computing capacity, speed and storing capability because of the technological progress that has occurred between the two years and which is built into the computers. As this example shows, to benefit from embodied technical change one has to invest in new capital goods. This is not the case with disembodied technical change.

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[1] While this is obvious with respect to computers it is somewhat less transparent regarding R&D expenditures. The latter, however, are just outlays for specific types of equipment and specific labor, which together produce an intermediate output – reflected in, e.g., patents – that is used in a later stage of the production process.
[2] As argued by Mellander (1999), a simple, albeit very crude, indicator of technical change that escapes this objection is a simple time trend.
[3] At the same time, the demand for unskilled labor decreases, due to unskilled labor and capital being substitutes.This reinforces the effect on the skill premium.

Disembodied technical change is not tied to capital or any other factor of production. From the perspective of an individual producer it can be viewed as an exogenous change, which at (virtually) no cost provides access to a superior production technology. An example of disembodied technical change is a new procedure for organizing the production process, like the introduction of the assembly line in the beginning of the 20th century, or the more recent just-in-time work organization schemes. As these changes amount to more efficient use of the prevailing factors of production, one can benefit from them without having to make any investments; one just has to get to know about the new procedures, which soon enough become common knowledge. It is important to note that the fact that disembodied technical is not channeled through a specific factor of production does not preclude that it might affect factors of production differently. If that is the case, the disembodied technical change is said to be non-neutral, cf. Binswanger (1974). In the context of disembodied technical change, skill-biased technical change can be defined as non-neutral technical change inducing a relative increase in the demand for skilled labor, *ceteris paribus*.

Implicitly, the explanation put forward by Krusell et al. (2000) presumes that technical change is embodied. In this case, investments in new capital, like computers, will imply increases in the capital-skilled labor ratios for two reasons: first, there are more units of capital per worker and, second, the most recent capital units are more effective than the older units. These two changes will reinforce one another in increasing the demand for skilled workers. Empirically, it will not be meaningful to try to distinguish between capital-skill complementarity and skill-biased technical change; the two will be observationally equivalent.

If, however, technical change is disembodied in nature then capital-skill complementarity and skill-biased technical change will be two completely separate phenomena. In this context, technical change can increase the demand for skilled labor even without capital investments and even if capital and skilled labor are substitutes. Conversely, if skilled labor and capital are complements then capital investments will increase the demand for labor but that will have nothing to do with technical change.

Thus, to be able to judge the importance of capital-skill complementarity for explaining the increase in the wage premium of skilled labor it is necessary to try to assess the relative importance of embodied and disembodied technical change. If all technical change is embodied, then capital-skill complementarity is *the* explanation.

If, one the other hand, a large part of technical change is disembodied then capital-skill complementarity is only part of the explanation.

Interestingly, there is no discussion about the distinction between embodied and disembodied technical change in the study by Krusell et al. (2000).[4] Moreover, the production technology assumed in the empirical analysis – a CES technology – does not allow capital and skilled labor to be complements. It only allows for capital-skill complementarity in a weak sense, namely by allowing the elasticity of substitution between capital and skilled labor to be smaller than the elasticity of substitution between capital and unskilled labor.

This study is an attempt to explicitly consider the two features of the Krusell et al. (2000) study just discussed, i.e. whether technical change is embodied and/or disembodied and whether capital and skilled labor are indeed complements. In order for capital-skill complementarity to be a good proxy to skill-biased technical change two facts have to be investigated: (i) that there is no disembodied technical change, and (ii) that capital-skill complementarity exists.

To be able to explicitly allow for embodied technical change, it is necessary to implement a so-called vintage model of capital; cf. Solow (1959). The distinguishing features of a vintage model is that investments are not only defined by capital expenditures; as the additions to the firm's capital are assumed to be more productive the more recently they have been made, the capital expenditures have to be *dated*. In a strict sense, this means that every investment corresponds to a unique capital object, a property that makes empirical modeling very complicated. However, Nelson (1964) has formulated an elegant approximation to the vintage model that is much easier to implement and which will be used in this study.[5] The focus of my analysis of embodied technical change will be on computer-equipment capital. This is because computers are good reflectors of technical change. Other kinds of capital – non-computer equipment and buildings – will be modeled by means of (perpetual inventory type) capital stock measures which do not distinguish between investments made at different points in time.

To allow different categories of labor to be either substitutes or complements, the production technology will be modeled by means of flexible functional form, the

[4] The same is true for the analysis by Lindquist (2001) where the model by Krusell et al. (2000) is applied to Swedish data.

[5] Nelson's formulation has been used in several papers aimed at estimating the effects of embodied technical change. See, e.g., You (1976) and McHugh and Lane (1983, 1987a,b).

translog production function [Christensen et al. (1973)]. This function also makes it possible to model non-neutral disembodied, and embodied technical change.

As far as I know, this is the first study integrating embodied and disembodied technical change into one and the same model within the context of investigating their effects on the demand for labor, thus making it possible to assess the relative importance of these two forms of technical change. Another contribution is that the integration of embodied and disembodied technical change is conducted within the framework of flexible functional form imposing few a priori constraints on the production technology.

The empirical analysis relies on data for 14 industries in the Swedish manufacturing sector 1985-1995. Three different cases are examined. In one all technical change is assumed to be disembodied while in another only disembodied technical change is considered. The third case simultaneously allows for embodied and disembodied technical change. This set-up makes it possible to establish if the omission of either one of the two types of technical change, or the inclusion of both, affect the results. As an indicator of disembodied technical change, a measure of the total use of information and communication technology in the Swedish economy will be used. As this measure is defined for the entire economy it should be possible to treat it as an exogenous variable at the industry level where the empirical analysis is conducted. Another advantage is that this specification makes the comparison between disembodied and embodied technical change "fair" in the sense that both types of technical change relate to the same phenomenon, namely the introduction of information and communication technology.

The analysis provides evidence that disembodied technical change is part of the explanation for the increases in the demand for skilled labor. In other words, not all of the technical change is of the embodied nature, which implies that capital-skill complementarity can thus not be all of the explanation for skill-biased technical change. Further, we find that computers and skilled labor seem to be complements, but there seems to be a sort of equipment-skill substitutability present in general. So, capital-skill complementarity could in our case be an explanation of skill-biased technical change in the case of computer equipment capital and not in that of equipment capital. Another of the important results of the analysis is that there exists a sort of negative skill-bias associated with embodied technical change. In other words, embodied technical change seems to be more favorable to a worker the lower his/her skills (determined by the education level). An explanation to this finding could be found in Goldin, and Katz (1996). According to them manufacturing have two distinct stages: (i) the machine-installation and machine-maintenance segment in which skilled workers and capital are always complements, and (ii) the production or assembly segment in which unskilled labor and capital are complements. If the machine-maintenance demand for skilled labor is offset by the production-process demand for unskilled labor by the adoption of the new technology, then the relative demand for skilled workers will decrease. This could provide an explanation of the found negative skill-bias associated with embodied technical change.

This paper is organized as follows: Next chapter provides a literature review. A brief description of the data is offered in Section 3 and in Section 4 the set-up of the model is described. Section 5 contains the results and Section 6 provides the conclusions.

2. Literature review

2.1. Skill-biased technical change literature

There is an extensive literature about the changes in the skill structure of labor demand and the impact of technical change on the demand for skilled workers. A comprehensive survey of these studies can be found in Chennels and Van Reenen (1999). I will in this section mention a few of these studies.

A strand of this literature, uses the method of first decomposing the aggregate change of the share of skilled labor into within- and between-units changes and then examine the impact of observable proxies for technical change on the within units skill changes. Berman, Bound, and Griliches (1994) introduced this method and applied it on the industry level. They found that the shift in demand for more-skilled workers since the beginning of the 1980s is mostly driven by within-industry rather than between-industry changes. They argue that the evidence found in their paper seems consistent with the view that biased technological change played a dominant role in skill upgrading. Autor Katz, and Krueger (1998) strengthen this result by concluding that the vast majority of the secular growth in the share of college graduates in U.S. manufacturing can be attributed to within-industry changes. They show that more computer intensive industries have had a greater rate of skill upgrading. They concluded that whatever is driving the rapid rate of within-industry skill upgrading over the past few decades is concentrated in the most computer-intensive sectors of the economy.

Except for the U.S. there are evidence from other countries as well. Machin and Van Reenen (1998) conclude that the increase in the wage bill share of nonproduction workers in the manufacturing sectors of seven OECD countries (United States, Denmark, France, Germany, Japan, Sweden and the United Kingdom) has occurred mainly within industries.

Studies in which the authors have applied the decomposition analysis into establishment level represent a further extension of this strand of literature. Dunne, Haltiwanger and Troske (1996) is one such study in which it is found that the aggregate change in the non-production labor share in the US manufacturing sector during 1972-1987 is dominated by within plant changes in the non-production labor share. Other studies yield similar results for other countries; cf. Haskel and Heden (1999) for the case of U.K and Aguirregabiria and Alonso-Borrego (2001) for the case of Spain.

In the literature about how industry and plant-level skill upgrading is affected by technical change there has been a variety of proxies used for technical change. Bartel and Lichtenberg (1987) estimate a restricted variable cost function for U.S. manufacturing industries for 1960, 1970, and 1980 and examine the impact of the age of capital on the share of highly educated workers. They find a positive association between younger capital and the share of highly educated workers and conclude that this provides strong support for the hypothesis that highly educated workers have a superior ability to adopt the new technology. Furthermore, they find that the impact of the age of capital on the share of educated workers is more pronounced in R&D intensive industries. In a similar spirit, Chun (2003) uses the age of IT capital as a proxy for the adoption of IT, but he also uses the IT capital stock as a proxy for the use of IT. A notable feature of his analysis is that he assumes all kinds of capital including that of computers to be quasi-fixed, i.e. fixed in the short run (one year). He divides workers into educated (college equivalents) and less educated (high school equivalents), and concludes that the use of IT is complementary with educated workers and that educated workers have a comparative advantage in the adoption of IT. In some of his model specifications he includes a measure of R&D expenditure to output, and finds a positive relationship of this measure and the relative demand for educated workers.

Berndt, Morrison and Rosenblum (1992) examined the impact of investments in high-tech capital on the demand for skilled labor. In their paper they examine how the share of non-production workers in total employment is affected by a capital-intensity measure and a measure of the share of high-tech capital in total capital. They found that skill upgrading towards more educated workers occurs along with increases in the ratio of high-tech capital in total capital. Berman, Bound, and Griliches (1994) examined the within industry skill upgrading in the U.S. manufacturing sector during the 1980´s. As their proxy for (exogenous) technical change they used the share of computer investments and the share of R&D expenditures. They found that the increase in non-production labor input is positively correlated with these measures. Autor Katz, and Krueger (1998) examine the impact of technical change on the within industry shifts toward more educated workers. They use indicators such as employee computer usage, computer capital per worker, and the rate of computer investment and show that approximately one-third of the increase in within-industry skill upgrading in US manufacturing from the 1980´s and 1970´s can be attributed to these measures. Further they show that the R&D over sales ratio has had a substantial positive impact on skill upgrading.

Proxies for skill-biased technical change are also investigated at the plant level. Dunne, Haltiwanger and Troske (1996) use data on U.S. manufacturing plants form the years 1972-1998. As technology indicators they use a firm level measure of the R&D stock and changes in ownership structure. They find significant R&D skill complementarity and a positive correlation of changes in the ownership structure with the increase in the nonproduction labor share. Another paper using plant level data is that of Doms, Dunne and Troske (1997). In this paper the authors use information on adoption and use of new automation technologies. When using cross section estimation for the year 1988 they find evidence that plants that use a large number of new technologies employ relatively more educated workers. On the other hand, when controlling for the plant specific fixed effect using data for the period 1977-1992 they do not find evidence that adoption of technology has any impact on the increase in the non-production worker share within plants.

There are several studies from other countries than the U.S., explaining the impact of various technology variables on changes in the share of skilled labor. Hansson (1996) examines and finds evidence of skill-biased technical change for the case of Sweden. He finds that R&D intensive industries and industries with high shares of technicians have been more likely to increase their share of skilled labor. Mellander (1999) controlling for a number of educational and demographic characteristics, also finds evidence of skill biased technical change for the case of Sweden. In his paper he uses a time trend as an indicator of technical change. This proxy for technical change is also used in Lindquist, and Skjerpen (2000) for the case of Norway.[6] Both of these studied find evidence of skill-biased technical change. In their study of the U.K., Haskel and Heden (1999) disaggregate labor into manual (more educated) and non-manual (less educated) and find that computers seem to be altering the production process away from manual labor rather than away from less educated labor. By using an estimated level of computer investments in the U.S. industry as an instrument in order to control for the endogeneity of computerization they confirm the robustness of these results. Aguirregabiria, and Alonso-Borrego (2001) examine Spanish firms for the manufacturing sector for the years 1986-1991. They estimate labor demand functions for white- and blue-collar workers. They break down white-collar workers into four occupations namely managers, professionals, commercials, and clerical workers. The stock of R&D capital, and the stock of technological capital (based on successful innovations externally generated and purchased by the firm) as well as a measure of adoption of R&D and technological capital are used as indicators of the technology. They find small and imprecise elasticities with respect to R&D capital, adoption of R&D and technological capital. As for the adoption of technical capital it seems to increase the demand for commercial workers and lower that of blue-collar workers.

In recent years there has been an interest of studying how technical change is related to organizational changes in firms´ production process. Bresnahan, Brynjolfsson and Hitt (2002) examine data for 300 large U.S. firms. They find that increased demand for skilled labor is complementary with information technology, organizational change, and new products and services. Caroli and Van Reenen (2001) use a panel of British and French establishments to investigate the effects of organizational changes on skill upgrading. They offer support for the hypothesis of skill-biased organizational change by finding first of all that organizational changes reduce the demand for unskilled workers in both countries. Secondly, they find that organizational changes are negatively associated with increases in regional skill price

[6] In Mellander (1999) the time trend is labor-type specific, while in the case of Lindquist, and Skjerpen (2000), the time trend is industry specific.

differentials (a measure of the relative supply of skill). The third of their findings is that organizational changes lead to greater productivity increases in establishments with larger initial skill endowments.

In total one can say that there is evidence that the observed increase in the share of skilled workers has mainly occurred within sectors and plants. This lends support to the hypothesis that technical change could explain the increase in the demand for skilled workers in total employment. Several studies try to corroborate the effect of technical change on the demand for skilled labor by including measures of R&D intensity and computerization in labor demand equations. While positive relations are often found, the use of these variables runs the risk of introducing endogeneity problems, which makes it hard to judge the results. In this strand of literature there is no discussion about the distinction between embodied and disembodied technical change.

2.2. Embodied technical change literature

As mentioned earlier there is no paper as far as I know that tries to explicitly investigate the relation between embodied technical change and the skill-biased technical change. Solow (1959) was the first one to introduce the concept of embodied technical change. The embodied nature of a substantial fraction of technical progress was considered unimportant by Denison (1964) and irrelevant in the long run by Phelps (1962). However, in recent years theoretical and empirical contributions to growth and business cycle theory have shown the importance of embodied technical change for explaining several stylized facts of the U.S. economy, such as the productivity slowdown, the decline in the relative price of investment goods and the persistent rise in the equipment to output ratio.[7] It is also shown that the nature of technical progress is relevant to understanding the labor market, in particular its implications on unemployment, and job creation and destruction.[8]

A shortcoming in the discussion about embodied technical change has been the lack of reliable estimates of the rate of technical change that is embodied in equipment capital. One could divide this strand of literature into two camps, that of the price-based, and that of the production-based estimates of embodied technical

[7] See Boucekkine, del Rio and Licandro (1999), Greenwood and Yorukoglu (1997), Hornstein and Krusell (1996), among others.
[8] See for e.g. del Rio (2001).

change. The first camp uses Gordon´s (1990) quality-adjusted price indices for producers´ durable equipment (PDE) in order to identify embodied technical change. The relative rate of decline of Gordon´s (1990) equipment price deflators puts the annual rate of embodied technical change no higher than 4%. Hornstein and Krusell (1996), Gort and Wall (1998) and others argue that these price-based estimates are likely to understate the true rate of embodied technical change. Further, some economists have argued that the advent of information technology and its incorporation has slowly pushed the average rate of embodied technical change higher (see Greenwood and Yorukoglu (1997), among others).

The second camp uses data on production and capital stock age using an approach due to Nelson (1964). The estimates found within this camp are five to seven times higher than the price-based estimates. For instance, the results of Bahk and Gort (1993) correspond to a 15-21 percent annual rate of growth of embodied technical change. A recent paper by Hobijn (2001) is an interesting addition in this strand of literature. Using data from 4-digit U.S. manufacturing industries he estimates the rate of embodied technical change to be around 12 percent, by means of an Euler investment equation. This figure is very close to that of Sakellaris and Wilson (2001), who develop a production-side approach that provides alternative estimates of embodied technical change without relying on accurate measurement of price indices for producer durable equipment. They find that the annual rate of embodied technical change is between 8 and 17 percent with their preferred estimate being 12 percent.

3. Data

The data used covers 14 industries in the Swedish manufacturing sector for the period 1985-1995. The codes and names of the industries considered are given in detail in Table 1 below. As an indicator of the relative size of the industries, Table 1 provides us with the employment share of each industry for the midpoint of the observation period, year 1990.

The data used are produced by Statistics Sweden and include the Swedish National Accounts (NA), the Employment Register (ER), the Labor Force Surveys (LFS), various Investment Surveys (IS) and the Trade Statistics (TS). The breakdown of the IT investments provided in the IS determines the cross-sectional dimension of

Table 1: The industries considered and their shares in total manufacturing employment in 1990.

Industry code	Industry	Employment share 1990, %
3100	Food, Beverages and Tobacco	9.0
3200	Textile, Apparel & Leather	3.1
3300	Saw, Mills and Wood Products	8.4
3400	Pulp, Paper and Printing & Publishing	14.2
3500	Chemical, Plastic Products and Petroleum	7.8
3600	Non-Metallic Mineral Products	5.1
3700	Basic Metals	3.9
3810	Metal Products	12.3
3820	Machinery & Equipment, not elsewhere classified	13.0
3830	Electrical Machinery, not elsewhere classified	7.9
3840	Transport Equipment, except Shipyards	11.7
3850	Instruments, Photographic & Optical Devices	2.1
3860	Shipyards	0.8
3900	Other Manufacturing	0.7
3000	Total Manufacturing	100.0

Note: The classification system used here SNI69, is very close to the ISIC codes.

the data. The starting point for the data is given by the first year of the ER, and a change in the industrial classification system has made it impossible to extend the time series beyond 1995.[9]

3.1. Capital stocks

When it comes to data on capital, we will have three different categories: computer equipment capital, non-computer equipment capital, and structure capital (buildings). The net capital stocks on equipment and structures are from the national accounts (NA) from Statistics Sweden[10] and are computed according to the Perpetual Inventory method. The variation across industries in the depreciation rates is considerably higher than the variation over time. Thus, the capital stock can be very close approximated by:

$$K_{ij,t} = (1 - \bar{d}_{ij})K_{ij,t-1} + I_{ij,t-1}$$

Where $K_{ij,t}$ is the capital stock of type i, in industry j, at the beginning of period t. The time-average SNA depreciation rate for capital of type i in industry j, is

[9] More details about the data can be found in A.1. in the Appendix.
[10] Two types of stocks are published by the SNA, namely "gross stocks" and "net stocks". For our purposes, the latter differ from the former in that the assumed rates of depreciation are consistently higher for the net stocks than for the corresponding gross stocks.

represented by the $\bar{d}_{ij}$, and $I_{ij,t-1}$ denotes gross investments in capital of type i in industry j during period t-1.

Table 2: Gross investment shares in Swedish manufacturing, 1985, 1990, and 1995 (% of total investments).

Industry	Computers			Equipment			Structures		
	1985	1990	1994	1985	1990	1994	1985	1990	1994
3100	3.4	4.8	17.0	68.8	73.2	67.1	27.8	22.0	15.9
3200	4.7	7.8	27.1	76.0	44.5	61.4	19.3	47.8	11.5
3300	4.4	8.1	25.0	70.2	69.5	54.7	25.4	22.5	20.2
3400	4.5	17.6	28.0	79.6	64.0	57.4	15.9	18.4	14.6
3500	2.7	9.3	23.5	77.6	69.9	54.0	19.8	20.7	22.5
3600	1.8	6.1	14.7	86.0	67.2	71.6	12.2	26.7	13.7
3700	3.6	29.4	24.1	85.7	61.6	66.1	10.7	8.9	9.7
3810	8.4	12.3	34.7	68.0	65.4	51.4	23.6	22.2	13.8
3820	13.4	27.3	38.4	60.8	63.1	52.5	25.8	9.6	9.1
3830	12.3	19.6	70.3	69.9	62.4	19.8	17.8	17.9	9.9
3840	9.2	26.6	81.1	63.2	50.6	13.0	27.6	22.8	5.9
3850	11.7	10.0	37.8	70.3	69.6	53.4	18.0	20.4	8.8
3860	3.3	15.7	26.3	65.6	39.1	38.2	31.1	45.2	35.5
3900	1.5	5.7	6.2	58.7	65.8	81.6	39.8	28.5	12.2
3000	6.4	16.8	37.6	72.3	63.3	48.1	21.3	19.9	14.3

Table 2 provides us with the development of the gross investment shares for the different types of capital over time. As can be seen from the table above the share of computer investments in total investments has in many industries more than doubled from 1985 to 1990. The increase was largest for industries 3700= Basic Metals, and 3860= Shipyards. Further, we see that all industries have doubled their share in 1994 compared to 1985. The largest increase occurred in 3840= Transport Equipment, except Shipyards, 3500= Chemical, Plastic Products and Petroleum, 3600= Non-Metallic Mineral Products, and in 3860= Shipyards.

As mentioned earlier the computer has been widely used as an “indicator” of technical progress and thus distinguishing it from the other types of capital is crucial for our analysis. The investment surveys (IS) provided by Statistics Sweden provide information on computer investments making it possible to brake down the equipment capital stock into computer capital stock and the stock of non-computer equipment.[11] The computer investment data include investments made for office use as well for use

[11] A detailed description of the computation of the computer capital stock and the corresponding rental prices can be found in the Appendix.

in the production process, e.g., CNC (computer numerically controlled) equipment and CAD/CAM – systems.[12]

Table 3: Capital stock shares in Swedish manufacturing, 1985, 1990, and 1995 (% of total capital).

Industry	Computers			Equipment			Structures		
	1985	1990	1995	1985	1990	1995	1985	1990	1995
3100	2.8	5.5	9.5	48.6	48.8	48.3	48.6	45.7	42.2
3200	3.5	6.6	9.2	60.7	56.4	46.4	35.9	37.0	44.4
3300	3.0	17.2	14.7	47.1	33.2	37.7	49.9	49.6	47.6
3400	9.2	13.8	16.8	56.0	54.2	51.4	34.8	32.0	31.7
3500	4.0	7.0	15.6	61.4	60.4	52.4	34.6	32.6	32.0
3600	2.0	6.1	6.9	50.8	50.5	49.3	47.2	43.4	43.8
3700	2.2	9.9	11.2	56.6	50.6	52.0	41.2	39.4	36.8
3810	8.8	18.0	19.5	44.8	41.0	41.4	46.5	41.0	39.2
3820	13.4	17.8	24.5	33.5	42.0	38.2	53.1	40.1	37.2
3830	16.1	16.2	44.5	41.7	48.5	24.2	42.2	35.3	31.2
3840	19.7	21.0	44.2	30.0	36.0	20.4	50.4	43.0	35.4
3850	23.6	15.7	29.8	39.7	56.4	43.5	36.7	27.9	26.8
3860	1.9	3.1	12.2	42.3	34.9	27.5	55.8	62.0	60.4
3900	2.1	5.0	5.7	37.6	38.9	36.3	60.4	56.2	58.0
3000	7.9	13.4	21.4	49.2	47.8	42.1	42.9	38.9	36.4

The average rates of depreciation for equipment capital in the NA are between 16 and 21 percent. Unfortunately there are no depreciation rates given for computer capital in the Swedish national accounts. Therefore I chose a depreciation rate very close to that used by the U.S. Bureau of Economic Analysis (1997) for office, computing and accounting equipment.[13] This rate equals 0.31 from 1978 forward and therefore a constant rate of depreciation of 1/3 for the estimation of computer equipment capital does not seem unreasonable in my case.

Due to the high depreciation rate for computers, the development of the computer capital stock shares is less dramatic than those of the investment shares as can be seen by comparing Table 2 and Table 3. This is especially true for the period of the early 1990`s. For the entire period though, the increase of the stock shares of computers are still quite remarkable. Except for three industries all industries have doubled, or more than doubled, their share in 1995 compared to 1985.

[12] More details can be found in Gunnarson et al. (2001).

[13] For details on computer depreciation patterns, see Oliner (1994), Oliner and Sichel (1994), and Fraumeni (1997).

3.2. Human capital data

The human capital data will provide information about workers and their level of education. I will distinguish among four types of labor with the following education levels: (1) Elementary school (compulsory shorter than 9 years), (2) 9 years compulsory school, (4) Upper secondary school, and (4) Tertiary and postgraduate education. Skilled labor category is defined by education level 3 and 4.

Table 4: Employment shares in Swedish manufacturing, 1985, 1990, and 1994 (% out of total employment).

Level of education	Year		
	1985	1990	1994
Less than 9 years	30	22	18
9 years	19	17	16
Upper secondary	42	48	51
Tertiary	9	13	16
Sum	100	100	100

From Table 4 we see that the shares of those with upper secondary and tertiary schooling has increased over the years, while that of those with less than 9 years and 9 years of schooling has decreased over time.

3.3. Measures of the age of computer equipment capital and IT use

When incorporating embodied technical change in the model we will have to make use of the age of computer equipment capital. This is going to be measured in the following way:

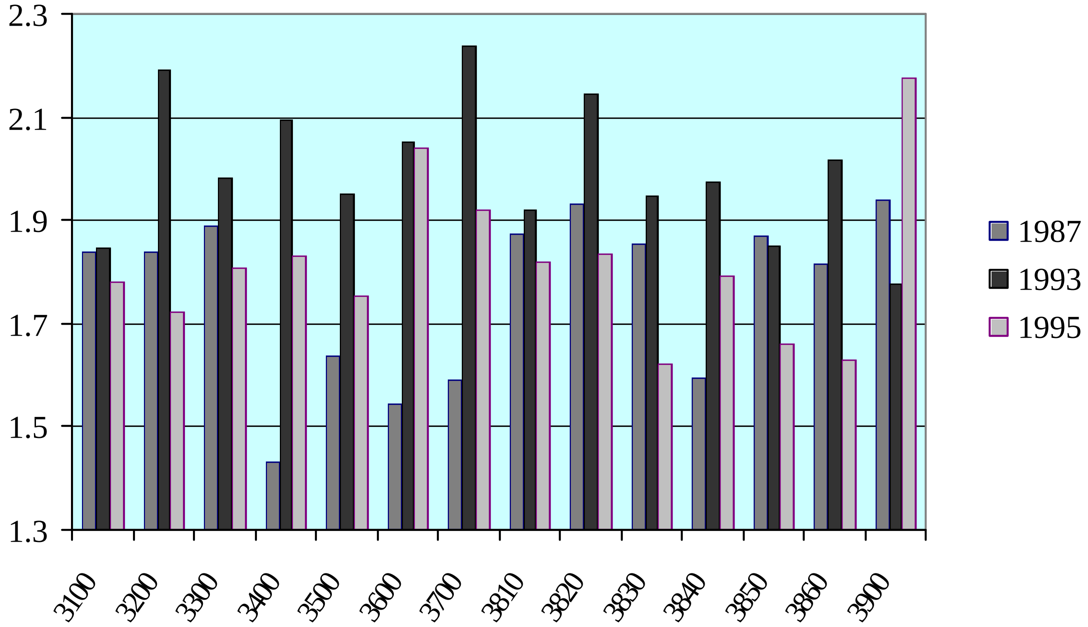
$$G_t = \frac{\sum_{v=0}^{t} (t-v) I_v}{K_t}$$

and

$$\sum_{v=0}^{t} I_v = K_t$$

where I_v is the net investment of computer equipment capital of vintage v. In the estimation of the age of computer equipment variable we have again assumed a depreciation rate of 1/3.

Figure 1: Average age of computer equipment capital, 1987, 1993, and 1995

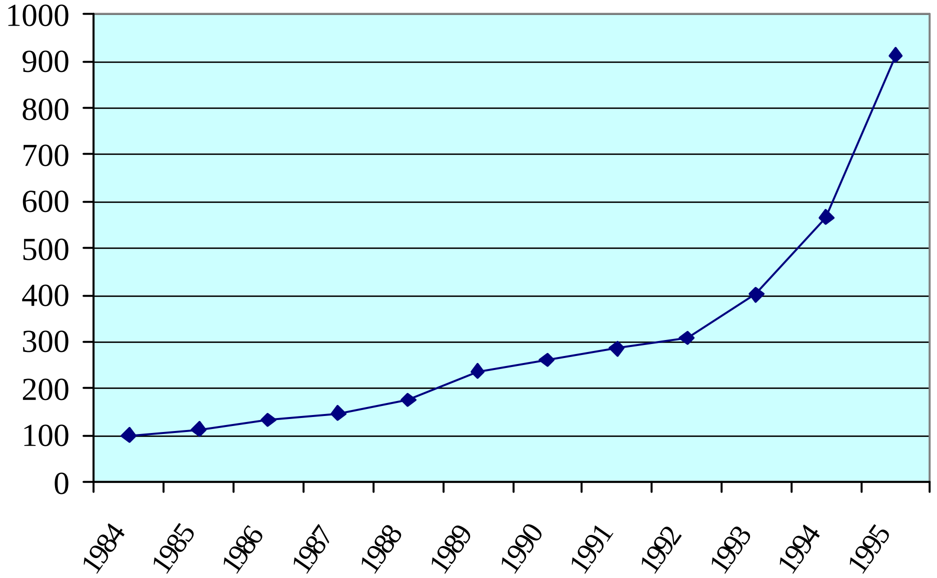


As can be seen from Figure 1, there is both time series and cross-sectional variation in the average age of the computer equipment capital. Further, the average age of capital is lower in year 1987 compared to year 1993 in 11 out of 14 industries.

An explanation of this fact could be that there was "overinvestment " in computer capital in 1987 leading to the computer capital stock being too large. This fact might have lead firms to invest less in computers the following years, leading to a higher average age of computers (this is the case for year 1993). Eventually though, firms would have to increase their investments in computers which would cause a fall in the average age in computer capital. The latter is reflected in Figure 1 by the fact that in 1995 the average age of computers in almost all of the industries seems to be lower compared to that of 1993.

Our measure of disembodied technical change will be the total use of IT, TUIT, depicted in Figure 2. This measure includes computers & peripherals, and communication equipment. The data on production, imports and exports are all in fixed (1991) prices and thus measure the volume development of IT. As can be seen from Figure 2 this measure has had a remarkable development over time. This is especially true after 1992. Between 1992 and 1995 the increase of TUIT was threefold.

Figure 2: Index of total use of IT in Sweden, 1984=100.



4. Set-up of the model

4.1. Technical change

The two views of technical change, namely that of embodied and disembodied, differ distinctively in their treatment of capital. In models of disembodied technical change the concept of capital is one in which investment goods of different generations (or "vintages") differ only by some fixed factor associated with wear, tear, and retirement. If we assume for simplicity that the loss of productive efficiency due to such wear and tear proceeds at a constant rate d , then the amount of capital available at any point in time will be the weighted sum of the surviving vintages:

$$K_t = I_t + (1-d)I_{t-1} + ... + (1-d)^t I_0 \tag{1}$$

The d weights convert each vintage of investment into new-machine equivalents, so that one unit five-year-old capital is equivalent in production to $(1-d)^5$ units of new capital. Thus the stock K_t can be interpreted as the number of new machine equivalents implied by the stream of past investment.

The treatment of capital is different when considering the embodied view of technical change. According to that view successive vintages of investment also embody differences in technical design. The technology is not the same across vintages, but is improving over vintages. This assumption captures the intuitive notion that technical progress in, say, computers is linked to improvements in the design of new machines and that a computer of vintage 1990 will tend to be more efficient at producing output, ceteris paribus, than a machine of vintage 1980, even if there is no physical loss of capacity. In this view, capital stock computed as per equation (1), that is under the assumption that design improvements can be ignored, will tend to understate the true productivity of the capital stock.

In order to incorporate improvements in the quality of capital in my model, I will make use of a so-called vintage model introduced by Solow (1959). According to this model effective capital, X_{Jt}, can be written in the following way when one assumes that advancing technology permits the quality of new machines to improve at the annual rate l :[14]

$$X_{Jt} = \sum_{0}^{t} X_{K_{vt}} (1 + l)^{n} \tag{2}$$

X_J in the above equation is a quality-weighted number of machines with new machines given greater weight than old machines, reflecting the newer technology embodied in them. Here $X_{K_{vt}}$ is the amount of capital built in year n (of vintage n) that is still in use at time t, and λ represents the rate of embodied technical progress, i.e. the quality of new machines improves at λ percent a year. Nelson´s approximation formula of equation (2) is written in the following way[15]:

$$X_{Jt} = \mathrm{B}(1 + l)^{t} X_{K_t} (1 + l (G_0 - G_t)) \tag{3}$$

where $X_{K_{vt}}$ is gross capital stock at time t and G_t and G_0 its average age at times t and 0, respectively. The above simplification involves a single moment of the age distribution of capital and replaces an equation involving the full distribution of vintages.

In its continuous version, Nelson´s approximation formula can be written as:

$$X_{Jt} = \mathrm{B}' e^{lt} X_{Kt} e^{-l G_t} \tag{4}$$

where $B' \approx 1$. Taking the log of the above expression gives the following equation:

[14] In the analysis to follow for the rest of Section 4.1., I do not consider the rates of depreciation. Those will be taken into account though, when estimating the model.

[15] Nelson (1964) reports that his tests show that the approximation is very good.

$$\ell n X_{Jt} = \ell n X_K + l\,t - l\,G_t \qquad (5)$$

Equation (5) will be used in order to incorporate the effects of embodied technical change of computer equipment capital into the production function. This equation has a very intuitive explanation. When the age distribution of the capital stock is not changing over time the rate of growth of the quality-adjusted capital stock is represented by the first two terms. The third term provides an adjustment when the age distribution is changing. A given age distribution determines a given difference between average quality and the quality of new capital. If each old machine were one year older, the difference between average quality and new quality would be larger by l. More generally the change in the gap between average quality and the quality of new equipment is approximately equal to $-\,l\,G_t$.

4.2 The production function

The translog production function, which is a second-order Taylor´s series approximation in logarithms to an arbitrary production function, [Christensen et al. (1973)] will be used in the analysis. This functional form will enable us to incorporate the effects of embodied technical change into our model. It is further a flexible functional form, because it does not place any a priori restrictions on substitution possibilities among the factors of production. It allows some factors of production to be substitutes and others to be complements.

I will consider eight inputs: four different categories of labor, L_1, L_2, L_3, L_4, computer equipment capital, X_C, non-computer equipment capital, X_M, structure capital, X_S, and intermediate goods, X_{IG}. All of them are treated as variable inputs.[16]

The production technology is represented by the following constant returns to scale translog production function:

$$\ell n Q = \ell n a_0 + a_T \ell n t + \sum a_i \ell n X_i + \sum b_{it} \ell n X_i t + \tfrac{1}{2} \sum \sum b_{ij} \ell n X_i \ell n X_j \qquad (6)$$

where $i, j = L_1, L_2, L_3, L_4, J, M, S, IG$, and $b_{ij} = b_{ji}$

[16] Treating all inputs as variable and, thus, optimally adjustable within one year greatly simplifies the formulation and estimation of the model. Admittedly, the assumption can be questioned with respect to structure capital but this is not an input of primary interest here.

Disembodied technical change is both (Hicks-) neutral and non-neutral in the above equation. Embodied technical change is incorporated in equation (6) through the computer equipment capital using a variant of equation (5), namely:

$$\ell n X_J = l_C(t - G_t) + \ell n X_C \tag{7}$$

All input levels in (6) must be strictly positive, since otherwise $\ell n X_i$ or $\ell n X_i \to \infty$ and then output is not well defined.

Constant returns to scale imply the following restrictions:

$$\sum_j a_j = 1,\ \sum_i b_{ij} = \sum_j b_{ji} = \sum_i \sum_j b_{ij} = 0 \text{ for } i, j = L_1, L_2, L_3, L_4, C, M, S, IG$$

The marginal product of the inputs are denoted as follows:

$$\frac{\partial Q}{\partial X_i} \equiv f_{X_i} = \frac{Q}{X_i}\left(a_i + b_{it}t + b_{ii}\ell n X_i + \sum_j b_{ij}\ell n X_j + b_{iC} l_C(t - G_t) \right)$$

Here, l_C denotes the rate of embodied technical change of computers. The second order derivatives are given by:

$$f_{X_i X_i} = \frac{Q}{X_i^2}\left(b_{ii} + \left(a_i + b_{it}t + \sum_j b_{ij}\ell n X_j + b_{iC} l_C(t - G_t) - 1 \right)\left(a_i + b_{it}t + \sum_j b_{ij}\ell n X_j + b_{iC} l_C(t - G_t) - 1 \right) \right)$$

$$i, j = L_1, L_{21}, L_3, L_4, C, M, S, IG$$

$$f_{X_i X_j} = \frac{Q}{X_i X_j}\left(b_{ij} + \left(a_j + b_{jt}t + \sum_j b_{ij}\ell n X_j + b_{jC} l_C(t - G_t) - 1 \right)\left(a_j + b_{jt}t + \sum_j b_{ij}\ell n X_j + b_{jC} l_C(t - G_t) - 1 \right) \right)$$

$$i, j = L_1, L_{21}, L_3, L_4, C, M, S, IG$$

Further, $\partial Q/\partial X_i > 0$ must hold, since the economic region of a linearly homogeneous production function is characterized by strictly positive marginal productivities. With reference to (6) we have:

$$M_{X_i} = \frac{\partial \ell n Q}{\partial \ell n X_i} = \frac{\partial Q}{\partial X_i}\frac{X_i}{Q} > 0 \tag{8}$$

As can be seen above, all output elasticities must be positive. Assuming further that input and product markets are competitive, the necessary conditions for profit maximization are $\partial Q/\partial X_i = P_i$, where P_i is the factor price of the ith input relative to the price of output *Q*. Substituting this relationship into (8) we obtain:

$$M_{X_i} = \frac{\partial Q}{\partial X_i}\frac{X_i}{Q} = \frac{P_i X_i}{Q} > 0 \tag{9}$$

In other words, the logarithmic marginal product of the *i*th input is equal to its share in total revenue. And, by constant returns to scale, the revenue share of input *i* equals its share in total costs.

When defining the partial elasticity of substitution between inputs, the most common measure is the Allen partial elasticity of substitution (AES. This measure defines the percentage change in the ratio of the quantity of two factors to the percentage change in their price ratio when all other factors are allowed to adjust to their optimal levels. The AES is given by:

$$s_{ij} = \left(\sum_i f_i X_i / X_i X_j \right) / \left(| \bar{F}_{ij} | / | \bar{F} | \right) \tag{10}$$

where $| \bar{F} |$ is the determinant of the bordered Hessian

$$| \bar{F} | = \begin{vmatrix} 0 & f_{X_{L_1}} & f_{X_{L_2}} & f_{X_{L_3}} & f_{X_{L_4}} & f_{X_C} & f_{X_M} & f_{X_S} & f_{X_{IG}} \\ f_{X_{L_1}} & f_{X_{L_1} X_{L_1}} & f_{X_{L_1} X_{L_2}} & f_{X_{L_1} X_{L_3}} & f_{X_{L_1} X_{L_4}} & f_{X_{L_1} X_C} & f_{X_{L_1} X_M} & f_{X_{L_1} X_S} & f_{X_{L_1} X_{IG}} \\ f_{X_{L_2}} & f_{X_{L_2} X_{L_1}} & f_{X_{L_2} X_{L_2}} & f_{X_{L_2} X_{L_3}} & f_{X_{L_2} X_{L_4}} & f_{X_{L_2} X_C} & f_{X_{L_2} X_M} & f_{X_{L_2} X_S} & f_{X_{L_2} X_{IG}} \\ f_{X_{L_3}} & f_{X_{L_3} X_{L_1}} & f_{X_{L_3} X_{L_2}} & f_{X_{L_3} X_{L_3}} & f_{X_{L_3} X_{L_4}} & f_{X_{L_3} X_C} & f_{X_{L_3} X_M} & f_{X_{L_3} X_S} & f_{X_{L_3} X_{IG}} \\ f_{X_{L_4}} & f_{X_{L_4} X_{L_1}} & f_{X_{L_4} X_{L_2}} & f_{X_{L_4} X_{L_3}} & f_{X_{L_4} X_{L_4}} & f_{X_{L_4} X_C} & f_{X_{L_4} X_M} & f_{X_{L_4} X_S} & f_{X_{L_4} X_{IG}} \\ f_{X_C} & f_{X_C X_{L_1}} & f_{X_C X_{L_2}} & f_{X_C X_{L_3}} & f_{X_C X_{L_4}} & f_{X_C X_C} & f_{X_C X_M} & f_{X_C X_S} & f_{X_C X_{IG}} \\ f_{X_M} & f_{X_M X_{L_1}} & f_{X_M X_{L_2}} & f_{X_M X_{L_3}} & f_{X_M X_{L_4}} & f_{X_M X_C} & f_{X_M X_M} & f_{X_M X_S} & f_{X_M X_{IG}} \\ f_{X_S} & f_{X_S X_{L_1}} & f_{X_S X_{L_2}} & f_{X_S X_{L_3}} & f_{X_S X_{L_4}} & f_{X_S X_C} & f_{X_S X_M} & f_{X_S X_S} & f_{X_S X_{IG}} \\ f_{X_{IG}} & f_{X_{IG} X_{L_1}} & f_{X_{IG} X_{L_2}} & f_{X_{IG} X_{L_3}} & f_{X_{IG} X_{L_4}} & f_{X_{IG} X_C} & f_{X_{IG} X_M} & f_{X_{IG} X_S} & f_{X_{IG} X_{IG}} \end{vmatrix}$$

and $| \bar{F}_{ij} |$ is the cofactor of F_{ij} in $\bar{F}$. The assumption of linear homogeneity of (6) assures that $\sum_i f_i X_i \equiv Q$.

The AES is related to the standard cross-price elasticity in the following way:

$$h_{x_i p_j} \equiv \frac{\partial X_i}{\partial P_j} \frac{P_j}{X_i} = AES_{x_i p_j} * s_j \tag{11}$$

where s_j is the cost share of factor j.

Although the Allen partial elasticity of substitution has been used extensively, it does not always measure the effect of greatest interest [see for eg. Thompson and Taylor (1995)]. One such instance is when the cost share of the variable of interest is very small. This is the case with computer equipment that we focus on here. Relatively small variations in the cost share will then induce sizable variations in the estimates of the Allen elasticity of substitution. Furthermore, as Chambers (1988) pointed out, expression (11) is the "most compelling argument for ignoring the Allen measure in applied analysis. The interesting measure is $\left[h_{x_i p_j}\right]$- why disguise it by dividing it by a cost share? This question becomes all the more pointed when the best reason for doing so is that it yields a measure that can only be interpreted intuitively in terms of $\left[h_{x_i p_j}\right]$". For the abovementioned reasons I will only report the own- and cross price elasticities. Positive (negative) numbers of the cross price elasticities will indicate that the two goods are substitutes (complements).

4.3 The regression model

The stochastic version of the factor shares of my model can be expressed as follows:[17]

$$M_{X_i} = a_i + b_{it}t + \sum_j b_{ij}\ell nX_i + b_{iC}\,l_c(t - G_t) + u_i \tag{12}$$

where a_i is a constant, and $i, j = L_1, L_2, L_3, L_4, C, M, S, IG$. The disturbances in (12) can be attributed to a variety of forces, like, e.g., input markets that are not perfectly competitive, measurement errors, or random deviations from profit maximization on the part of firms.

The assumption of linear homogeneity of (6), together with the symmetry restrictions, makes it possible to limit our attention to the estimation of $M_{L_1}, M_{L_2}, M_{L_3}, M_{L_4}, M_M$, M_C, and M_{IG} only. This is because we are ensured that the parameter estimates of any seven of the eight equations in (12) will identify exactly all parameters of the production function.

Since the cost shares in (12) sum to unity at each observation, the parameter estimates must satisfy the following zero column sum restrictions:[18]

$$\sum_i a_i = 1,\ \sum_i b_{it} = 0,\ \sum_i \sum_j b_{ij} = 0,\ \sum_i b_{iC}\,l_C = 0 \tag{13}$$

Furthermore, we impose symmetry since the partial derivatives must be symmetric in inputs in order for (12) to be interpretable as the logarithmic marginal productivities of a well-defined production function. Imposing symmetry implies the following restriction:

$$b_{ij} = b_{ji},\ \forall i, j \tag{14}$$

[17] For an extensive form of equation (12), see A.2. in the Appendix.
[18] For an extensive form of the restrictions in (13), see A.3.in the Appendix.

The restriction of zero row sums of the b_{ij}´s requires that

$$\hat{b}_{ij} = -(\hat{b}_{ii} + \sum_{i} \hat{b}_{ik}) \text{ for } i, j, k = L_1, L_2, L_3, L_4, C, M, S, IG$$

Thus only 59 of the 80 parameters are unrestricted in (12).[19] Zero column sums (13) and symmetry (14) imply zero row sums; alternatively, zero row and column sums imply symmetry.

A potential problem in the estimation of the model is the fact that the translog does not satisfy monotonicity and quasi-concavity globally. Monotonicity of the translog requires the logarithmic marginal products to be positive for all inputs. Further, quasi-concavity implies that the bordered Hessian is associated with a negative definite quadratic form. It practice there is no unanimity of the minimum percentage of observations that should verify quasiconcavity and monotonicity so as to call a production function regular. The finding of acceptable regions satisfying the previously alluded properties is an empirical question.[20]

Next, we consider some estimation problems. First, we have to consider the fact that the estimates b_{ij} and b_{ji} (*i* not equal to *j*) for any two equations of the system (12) will not generally be equal. Thus we cannot estimate a set of unique parameters by applying least squares to each equation individually. The imposition of the symmetry and linear homogeneity restrictions allows us to estimate the following alternative equation:[21]

$$M_{X_i} = d_i + b_{it} t + \sum_{j} b_{ij} \ell n\left(\frac{X_j}{X_S}\right) + b_{iC}\, l_C (t - G_t) + u_i \tag{15}$$

$$i, j = L_1, L_2, L_3, L_4, C, M, IG$$

We can combine the above equations into a single regression equation of the following form:

$$A = B \times C + U \tag{16}$$

where A is a 7x1 vector, B is a 7x49 matrix, C is a 49x1 vector, and U is a 7x1 vector.

The disturbances in (15) are most likely correlated, because, e.g., deviations from profit maximization should affect all input demands. To yield more efficient

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[19] The extensive form of the restrictions can be found in A.4. in the Appendix.
[20] We will return to this question in the discussion of the results.
[21] For an extensive form of equation (15), see A.5. in the Appendix.

parameter estimates one can use Zellner´s two-stage estimation procedure. [22] This approach has also a potential problem, namely that the estimates obtained depend on the choice of the left out equation. One estimation procedure that does not suffer of this potential problem is maximum likelihood. Kmenta and Gilbert (1968) showed that iterative Zellner (IZEF) and maximum likelihood estimates are identical. Thus, by applying the IZEF method to equation (15) we obtain estimates that are asymptotic maximum-likelihood estimates and are therefore independent of which share equations we use.

As mentioned earlier the simplest way to capture disembodied technical change without running the risk to introduce edogeneity problem is to use a time trend. In general, however, the regression results will not be invariant with respect to the specification of the time trend. Here we employ index of the total use of IT in Sweden (TUIT) to capture disembodied technical change. For a given industry, this index should be exogenous, like a time trend. An advantage over the trend is that this index allows us to make a comparison between disembodied and embodied technical change that is associated only with computers. Equation (12) becomes:

$$M_{X_i} = a_i + b_{it} TUIT + \sum_j b_{ij} \ell n X_i + b_{iC} l_c (t - G_t) + u_i \tag{17}$$

where $i, j = L_1, L_2, L_3, L_4, C, M, S, IG$

In the estimation, 3 variants of equation (17) will be estimated. In the first one I will assume that there is only disembodied technical change. The second regression will present the case where all technical change is taken to be embodied and in the third regression I will allow for both embodied and disembodied technical change. In this way we will be able to establish if the omission of either one of the types of technical change will affect our results.

Since the primary interest of the current paper is not to estimate the rate of embodied technical change it will be set a priori to 0.15. This value of l is chosen after considering a grid of values within the estimated range of rates of embodied technical change found in the production-based camp of literature on the quantification of embodied technical change mentioned in the literature review. The

[22] See Zellner (1962).

grid search revealed that the chosen value of l maximizes the log likelihood function.

In the estimation of the system of input cost shares I will also include the production function in equation (6). That is:

$$\ell nQ = \ell n a_0 + a_T \ell nt + \sum a_i \ell nX_i + \sum b_{it} \ell nX_i t + \tfrac{1}{2} \sum \sum b_{ij} \ell nX_i \ell nX_j \qquad (18)$$

There are two reasons for including equation (18) in the estimation. The first is that it will make possible to identify the parameter a_T, which measures an important aspect of disembodied technical change, namely Hicks- neutral technical progress. The other reason for including (18) is that it adds degrees of freedom in the estimation and, thereby, increases the precision of the parameter estimates.

5. Results

In Table 5 I have only included the estimated parameters of the production function that relates to the effects of technical change for the inputs labor, computer and non-computer equipment capital.[23] Regression (I) corresponds to the case, where there is only disembodied technical change, measured by the TUIT variable.

As can be seen from Table 5 the yearly rate of neutral technical change is about 2% and highly significant. This result is in line with the estimates found in the studies by Mellander (1999) and Gunnarsson et al. (2001).

The estimates of disembodied skill-biased technical change are given by the b_{it}´s. As can be seen they are all significantly different from zero for the first three categories of labor, indicating that disembodied technical change should not be ruled out when estimating the effects of technical change. Further, we find support for the skill-biased technical change hypothesis. Technical change reduces the demand for workers with less than 9 years of education, and for those with 9 years of education while it increases the demand for those with upper secondary and tertiary education. The effects of technical change are increasing in magnitude when going from the lowest to the highest level of education for the first three categories of labor.

The estimates concerning disembodied technical change with respect to computer and non-computer equipment capital are positive and negative, respectively. The negative sign on b_{Ct} indicates that disembodied technical change has affected the

[23] The rest of the estimates are provided in Table 8 in the Appendix.

demand for computers in a negative way compared to a weighted average of the effects of disembodied technical change for all the other inputs. An explanation to this finding can perhaps be found in Morrison (1997). In her paper, she found that in the U.S. there was ”overinvestment” in IT during the latter half of the 1980s. The natural interpretation of the term ”overinvestment” here is in a relative sense, i.e. that IT investments were too large compared to outlays on other factors of production, notably human capital. Possibly, a similar development took place in Sweden, too. If so, the fact that the stock of computer capital was too large at the beginning of the period may well have led to a relative decrease in the demand for computers, especially when combined with the fact that disembodied technical change increased the demand for non-computer equipment.

The case where we have only embodied technical change is investigated in regression (II). In this case the estimates are all significantly different from zero except for the case of labor with upper secondary education. The results indicate that it is important to consider embodied technical change when estimating the effects of technical change. However, in regression (II) we do not find support for the skill-biased technical change hypothesis. It seems to be the case that embodied technical change is increasing the demand for workers with less than 9 years, 9 years of education and those with upper secondary education while decreasing that of workers with tertiary education. Thus, the opposite of what is true for disembodied technical change seems to be the case here. There is in the case of embodied technical change a sort of anti skill-biased technical change. That is to say that, embodied technical change seems to be more favorable to a worker the lower his/her level of the education.

A possible explanation of the found bias towards low skills can perhaps be found in Goldin and Katz (1996). As argued by them, manufacturing should be envisioned as having two distinct stages, namely: (i) a machine-installation and machine-maintenance segment, and (ii) a production or assembly portion. Skilled workers and capital are always complements in the machine-maintenance segment of manufacturing, creating workable capital. This capital is then used by unskilled labor in the production or assembly portion of manufacturing, where the creation of the final product occurs. “How the adoption of a technology alters the relative demand for skilled workers will depend on whether the machine-maintenance demand for skilled labor is offset by the production-process demand for unskilled labor.” [Goldin, and

Katz (1996)]. For the industries studied during this particular 10-year period, ranging from the mid-80´s to the mid 90´s, it seems that embodied technical change was such that the machine-installation and machine-maintenance aspect was dominated by the production or assembly dimension.

The argument found in Goldin, and Katz can perhaps be strengthened by the following argument. In manufacturing, the major part of computer capital consists of industry robots and computer numerically controlled (CNC) equipment. Unlike the case with a PC, the technical change embodied in this kind of capital may well reduce the need for skilled workers, rather than enhancing its productive capacity. In other

Table 5: Estimated parameters of technical change for labor, equipment capital and non-equipment computer capital.

	Regression I	Regression II	Regression III
a_T	0.02102*** (0.00448)	---	0.01949*** (0.00448)
b_{L_1t}	-0.00093* (0.00056)	---	-0.00133** (0.00056)
b_{L_2t}	-0.00043* (0.00024)	---	-0.00064* (0.00025)
b_{L_3t}	0.001537** (0.00075)	---	0.001064 (0.00076)
b_{L_4t}	0.000019 (0.00063)	---	0.000296 (0.00063)
b_{Mt}	0.002716*** (0.00047)	---	0.003048*** (0.00048)
b_{Ct}	-0.00049*** (0.00014)	---	-0.00106*** (0.00015)
$b_{L_1C} * l$	---	0.00091*** (0.00014)	0.00069*** (0.00015)
$b_{L_2C} * l$	---	0.00034*** (0.00007)	0.00028*** (0.00007)
$b_{L_3C} * l$	---	0.00016 (0.0002)	0.00014 (0.0002)
$b_{L_4C} * l$	---	-0.0008*** (0.00017)	-0.0007*** (0.00017)
$b_{MC} * l$	---	-0.00035*** (0.00012)	-0.0006*** (0.00012)
$b_{CC} * l$	---	0.00069*** (0.00005)	0.00079*** (0.00005)

Notes:
a)The absolute value of the standard errors,are given in the parentheses.
b)*,**, and*** denote significantly different from 0 at the 10%, 5%, and 1% level.
c) To save space the rest of the estimated parameters are reported in Table 8 in the Appendix.

words, the technical change embodied in the non-computer equipment capital may have taken over much of the sophisticated thinking previously needed from skilled workers. This might even be true with respect to the machine-installation and machine-maintenance portion of production previously run mainly by skilled labor. So, running and in many instances installing and maintaining this kind of new capital may not require the high skills needed by previous machines, but can be performed by less skilled labor. In new computer-based equipment, installation and maintenance are often very simple and self-instructive due to the use of routines created by means of computers.[24]

When it comes to the demand for computer and non-computer equipment capital embodied technical change had a positive effect on the former and a negative one on the latter. This is natural; with technical change being embodied, firms have to buy new computers in order to reap the benefits of technical change. The resulting relative increase in the demand for computers may well lead to a relative decrease in the demand for equipment capital.

In equation (III) I include both embodied and disembodied technical change. The results are fairly stable as can be seen from Table 5. In general one can say that both embodied and disembodied technical change can be estimated separately by regressions (I) and (II), respectively. The omission of either one of the types of technical change, or the inclusion of both in the model, does not seem to affect our results.

In order to be able to say something about the relative magnitude of the skill-biases, the elasticities for disembodied and embodied technical change are calculated according to the formulas:

$$e_{M_i,TUIT} = \frac{\partial M_i}{\partial TUIT}\frac{TUIT}{M_i} \quad \text{and } e_{M_i,t-G} = \frac{\partial M_i}{\partial (t-G)}\frac{(t-G)}{M_i}$$

where $i = L_1, L_2, L_3, L_4$ represents labor with education levels 1, 2, 3, and 4. The elasticities show how a 1% change in technical change (disembodied or embodied) affects the demand for the four different categories of labor respectively.

Table 6 displays the elasticities for the skill-biases for regression (III).[25] In the first part of the table, three industries 3300= Saw, Mills and Wood Products, 3400= Pulp,

[24] This argument points to the importance of extending the present analysis to the service sector. In services the distinction between maintenance and production is irrelevant implying that the effects of embodied technical change may be different.

[25] Being functions of estimated parameters, the elasticities are random variables. As the mappings from the parameter estimates to the elasticities are highly non-linear it is very difficult to compute standard errors for the elasticities, however. One simplification that would reduce the computations substantially

Paper and Printing and Publishing, and 3500= Chemical, Plastic Products and Petroleum, are investigated for the year 1993. Together, these three industries make up about 1/3 of the manufacturing sector, in terms of employment. There are no considerable differences between the effects of technical change on the different types of labor across the industries considered. An exception to this statement is perhaps the effects of disembodied and embodied technical change on labor with education level 4. The latter effects are about 70% higher for industry 3300 than for 3400 and 3500. When comparing the effects of the two types of technical change across the different types of labor we observe that the effects of embodied technical change are larger (in absolute value) than those of disembodied in three of the labor categories, namely those with education levels 1, 2, and 4.

Table 6: The elasticities of the skill-biases for regression III.

Year 1993:

	L1		L2		L3		L4	
Industry:	Disemb.	Embod.	Disemb.	Embod.	Disemb.	Embod.	Disemb.	Embod.
3300	-0.032	0.042	-0.024	0.026	0.019	0.006	0.024	-0.137
3400	-0.038	0.049	-0.020	0.021	0.012	0.004	0.007	-0.042
3500	-0.046	0.059	-0.025	0.028	0.014	0.005	0.006	-0.033

Industry 3500:

	L1		L2		L3		L4	
Year:	Disemb.	Embod.	Disemb.	Embod.	Disemb.	Embod.	Disemb.	Embod.
1987	-0.013	0.009	-0.008	0.005	0.005	0.001	0.003	-0.008
1990	-0.025	0.030	-0.015	0.015	0.009	0.003	0.004	-0.022
1993	-0.046	0.059	-0.025	0.028	0.014	0.005	0.006	-0.033

The second part of the table concerns industry 3500 for the years 1987, 1990 and 1993. We see that all effects increase in absolute value over time. When it comes to disembodied technical change, its negative effects on workers with education level 1 and 2 increase over time, and so does its positive effects on workers with education level 3 and 4. This means that in this case, the skill-biased technical change hypothesis is strengthened over time. As for embodied technical change, its positive effects on workers with education level 1, 2, and 3, and the negative effect on workers with education 4 also increase over time. The anti skill-biased technical change is strengthened over time. Also it seems that for labor of type 1, and 2, the effects of

would be to disregard the fact that the M_i´s are functions of the estimated parameters. This simplification can be justified on the ground that the estimated cost shares fit the data very well and so are very close to the actual shares.

embodied technical change became larger than those of disembodied (in absolute value) only in year 1993.

To sum up Table 6, one can say that the effects of embodied technical change seem to be larger (in absolute value) in general than those of disembodied technical change for the three industries considered here. One should note however that for at least industry 3500 this is a pattern observed only in the last year for labor with the two lowest levels of education. We should also mention here that the results provided in Table 6 are contingent upon our maintained assumption that the rate of embodied technical change is constant and equal to 15 percent per year.[26]. Finally, it should also be mentioned that elasticities of the skill-biases are very small in magnitude and range approximately between –0.01and 0.06.

Next, I investigate the relationship between the different types of inputs. In particular I report the elasticities of demand for labor, equipment capital and non-equipment capital in Table 7.[27] Again, first for year 1993 for industry 3300, 3400 and 3500 and then for industry 3500 for the years 1987, 1990, and 1993. What interests me the most are the relationships between skilled labor – defined by the two highest levels of education – and computer capital on the one hand, and skilled labor and non-computer equipment capital, on the other hand. These relationships differ somewhat as can be seen from Table 7.

For all industries there seems to be a relationship of substitutability between non-computer equipment capital and workers with education level 3. When it comes to workers with education level 4 their relationship with non-computer equipment capital seem in general to be substitutability. Workers with education level 3 (those with upper secondary schooling) are complements with computer equipment capital in industry 3300 and 3400 while substitutes in industry 3500. Complementarity exists also between computers and workers with tertiary education except for the case of industry 3400. For industry 3500, this relationship becomes weaker over time. Also,

[26] As noted above in Section 4.4 this rate of embodied technical change is determined by a grid search. However, the fact that it is taken to be constant over time, will imply that small variations in this rate will have only minor effects on the results.
[27] The requirement that the production function be quasi-convex in inputs implies, inter alia, that all own-price elasticities of demand should be negative. Unfortunately, there is no way to impose this constraint a priori and, empirically, it often turns out to be violated for a large part of the observations. In this study, more than 50% of the own-price elasticities were of the expected negative sign, which is quite good, given the very rich parametrical structure of the model. As only observations with negative own-price elasticities lend themselves to meaningful interpretations only such results have been chosen for Table 7.

by comparing the relationship between computers and workers with the two highest levels of education we notice that the degree of complementarity increases the higher the education level.

Table 7: Elasticities of demand for labor, equipment capital and non-equipment computer capital.

Price	Year 1993			Industry 3500		
Elasticity	Industry 3300	Industry3400	Industry 3500	1987	1990	1993
$h_{L_1L_1}$	-2.72	-3.71	-14.64	-3.95	-4.91	-14.64
$h_{L_1L_2}$	-0.10	0.96	4.15	0.71	1.18	4.15
$h_{L_1L_3}$	1.52	-2.59	12.71	3.69	3.39	12.71
$h_{L_1L_4}$	0.55	6.11	0.09	-0.32	0.52	0.09
h_{L_1M}	-2.67	1.63	-8.91	-2.04	-2.11	-8.91
h_{L_1C}	0.06	-1.28	-0.64	-0.13	-0.31	-0.64
$h_{L_2L_2}$	-3.60	-2.22	-4.54	-2.75	-2.91	-4.54
$h_{L_2L_1}$	-0.15	1.04	4.80	0.96	1.47	4.80
$h_{L_2L_3}$	3.39	2.04	-1.20	1.58	1.15	-1.20
$h_{L_2L_4}$	0.65	-1.59	-0.32	-0.32	-0.25	-0.32
h_{L_2M}	-1.82	-0.43	2.43	0.12	0.44	2.43
h_{L_2C}	-0.02	0.33	0.14	-0.01	0.03	0.14
$h_{L_3L_3}$	-3.00	-3.68	-7.46	-4.94	-3.23	-7.46
$h_{L_3L_1}$	1.14	-1.01	4.89	1.78	1.44	4.89
$h_{L_3L_2}$	1.67	0.74	-0.40	0.56	0.39	-0.40
$h_{L_3L_4}$	-1.13	5.13	0.31	0.83	-0.14	0.31
h_{L_3M}	4.18	2.91	3.65	1.74	0.98	3.65
h_{L_3C}	-0.06	-0.94	0.38	0.19	0.31	0.38
$h_{L_4L_4}$	-0.90	-24.16	-1.63	-2.61	-1.45	-1.63
$h_{L_4L_1}$	1.83	5.23	0.05	-0.29	0.39	0.05
$h_{L_4L_2}$	1.41	-1.26	-0.16	-0.21	-0.15	-0.16
$h_{L_4L_3}$	-4.94	11.25	0.46	1.57	-0.25	0.46
h_{L_4M}	5.32	-10.08	0.04	-0.41	0.51	0.04
h_{L_4C}	-0.53	4.51	-0.17	-0.20	-0.24	-0.17

In general one can say that computer equipment capital and skilled labor are complements, while non-computer equipment capital and skilled labor are substitutes. Thus, when speaking about the relation of capital and skilled labor it is important to distinguish between different kinds of capital.

6. Summary and concluding remarks

The objective of this study has been to analyze how the skill mix in labor demand is affected by technical changes, on the one hand, and by the relation between capital and labor, on the other hand. To this end, detailed production data for 14 industries in the Swedish manufacturing sector 1985-1995 have been used to simultaneously estimate a translog production function and input demand equations derived from that production function.

The major distinction between this and previous studies is the modeling of technical change: both embodied and disembodied technical changes are explicitly allowed for, within the same formal framework. Coupled with very detailed information on both labor and capital, this feature enables a thorough investigation of the relationship between two hypotheses concerning labor demand, namely Griliches (1969) hypothesis of capital-skill complementarity and the hypothesis of skill-biased technical change launched by Berman, Bound, and Griliches (1994). The investigation has been inspired by the claim of Krusell et al. (2000) that, in the US, skill-biased technical change and capital-skill complementarity have been essentially one and the same thing, a claim which has been extended to Swedish conditions by Lindquist (2001).

To summarize the results, the model's 8-input structure will here not be considered at full length. We will limit our attention to two labor and two categories of capital. The labor categories are those that can qualify as skilled labor, workers with upper secondary education and workers with tertiary education. The two types of capital that we will discuss are computers and (non-computer) equipment. Even with this aggregate input structure the number of permutations become large when each of the inputs are combined with the two kinds of technical change, embodied and disembodied. To further limit the discussion, we will not consider the results for all of the 14 industries but focus on three industries for which the estimated production function satisfies most of the regularity conditions that follow from economic theory. The industries are the sectors 3300 = Saw mills and wood products, 3400 = Pulp and paper & printing and publishing, and 3500 = Chemicals, plastics, and petroleum. Together, these industries make up about a third of the employment in Swedish manufacturing.

Regarding the relationships between labor and capital, we find that in two of these three industries (3300 and 3500) the most skilled workers (with tertiary education) are complements with computers, but substitutes with equipment. In industry 3400 the pattern is reversed, i.e. tertiary educated workers are substitutes with computers and complements with equipment. What we learn from this is that not even with respect to the most well-educated category of workers and the most sophisticated type of capital, i.e. computers, is there a clear pattern of capital-skill complementarity. Moreover, our results for equipment capital tell us that the notion of capital-skill complementarity has to be qualified with respect to the type of capital considered: only in one of the three industries (3400) are tertiary educated workers and equipment capital complements.

Stepping down the skill ladder, we see that the differences between the two categories of capital seem to be more important than the differences between the two kinds of skilled labor: qualitatively, the relations between workers with upper secondary education and computers and equipment, respectively, are very similar to what we find for workers with tertiary education.

Turning to the impacts of technical change on the demands for skilled workers our primary result is that both embodied and disembodied technical change matter. This implies that the common approach in empirical analyses, i.e. to assume that all technical change is either disembodied or embodied in nature may result in misleading inferences. Our results also show that the relative importance of embodied and disembodied technical change differs between workers with upper secondary education and workers with tertiary education. With respect to the former category disembodied technical change is more important for determining labor demand while embodied technical change dominates with respect to tertiary educated workers.

At this stage, an intermediate conclusion can be reached with respect to the claim put forward by Krusell et al. (2000) and Lindquist (2001): if one wants to make the argument that capital-skill complementarity is the explanation for skill-biased technical change, one has to qualify this argument carefully. There are two reasons for this conclusion, which relate to the necessary conditions for this argument to be valid. First of all, one necessary condition for the argument to hold is that skilled labor and capital really are complements. At best, this property is satisfied with respect to the very highest skilled workers and the most sophisticated capital, i.e. computers. Secondly, the other necessary condition, i.e. that there is only embodied technical change, does not hold with respect to our data. But, possibly it can be taken to be satisfied approximately with respect to the demand for the most skilled workers. In short, the empirical analysis in this study indicates that the explanation suggested by Krusell et al. (2000) may possibly be valid for university educated labor working with computers, but that it cannot be extended to other workers and other types of capital.

The abovementioned conditions are necessary but not sufficient when making the argument that capital-skill complementarity is the explanation for skill-biased technical change. An inspection of the estimated skill-biases further emphasizes the need for more nuance characterization of the relation between capital, skilled labor and technical change. This is so because our results show that with respect to most skilled category of labor the dominant skill bias in technical change – the one associated with embodied technical change – is *negative*. This result is in sharp contrast with previous studies which invariably have found the bias in technical change to be positive for the most highly skilled workers. Presumably, this difference is due to the much more general modeling framework used in this paper. [28]

One explanation for the finding of a negative skill bias for tertiary educated workers can be found in Goldin, and Katz (1996). They claimed that manufacturing should be envisioned as having two distinct stages, namely: (i) a machine-installation and machine-maintenance segment, and (ii) a production or assembly portion. Skilled workers and capital are always complements in the machine-maintenance segment of manufacturing, creating workable capital. That capital is then used by unskilled labor in the production or assembly portion of manufacturing, where the creation of the final product occurs. Embodied technical change seems to have been of the type favoring the production or assembly portion segment of manufacturing over the machine-installation and machine-maintenance portion, for the industries and the period studied. The above argument is strengthened even further if one assumes that a part of the machine-installation and machine-maintenance segment of production in the industries studied is probably run more and more by less skilled labor. This is because as the sophistication of the machines increases, they can perform many complex tasks previously done by skilled labor, in this way replacing the need for the thinking man. It should be noted though that this latter argument may well be invalid within a different setting and another time frame. Also, it is certainly conceivable that there are instances in which the argument explaining the negative high-skill bias in embodied technical change could be made in the opposite direction. What is worth noticing however is that it seems to be the case that not all kind of technical change is good for skilled labor in my case. The results seem also very stable in terms of the

[28] Consistent with this conjecture is that the (smaller) skill bias associated with disembodied technical change is positive with respect to tertiary educated workers, like in studies only allowing for disembodied technical change, see, e.g., Mellander (1999) and Lindquist and Skjerpen (2000).

different specifications of the model used. The omission of either one of the types of technical change, or the inclusion of both in the model does not seem to affect our results.

In judging the results one should keep in mind that the rate of embodied technical change of computers is kept constant in our model. As mentioned before, computers have seen a remarkable quality improvement embodied in them. Keeping in mind Moore´s law, which tell us that the number of transistors on a chip doubles every 18-24 months, a perhaps more realistic assumption in our model would be one which allowed for advances in the rate at which technology improves. The determination of an appropriate improvement rate could however represent a new modeling challenge.

It should also be remembered that our study is based on data ending quite a few years back. An extension of the data set might as well show that the results have changed during recent years. One should also remember that our results concern the manufacturing sector. A study of the service sector should perhaps provide us with a different outcome and would be an interesting extension to the study outlined in this paper.

REFERENCES

[1] Autor, David H., Lawrence F. Katz and Alan B. Kreuger (1998), "Computing Inequality: Have Computers Changed the Labor Market?", *Quarterly Journal of Economics*, 113(4), November, pp. 1169-1213.

[2] Aguirregabiria, V. and V. Alonso-Borrego (2001), "Occupational structure, technical innovation, and reorganization of production", *Labor Economics*, 8(1), pp. 43-73.

[3] Bahk, Byong-Hyong and Michael Gort (1993), "Decomposing Learning by Doing in New Plants", *Journal of Political Economy*, 101(4), August, pp. 561-83.

[4] Bartel, Ann P. and Frank R. Lichtenberg (1987), "The Comparative Advantage of Educated Workers in Implementing New Technology", *Review of Economics and Statistics*, 69, pp. 1-11.

[5] Berman, Eli B. and John Griliches (1994), "Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures", *Quarterly Journal of Economics*, 109(2), May, pp. 367-97.

[6] Berndt, Ernst R., Catherine J. Morrison and Larry S. Rosenblum (1992), "High-Tech Capital Formation and Labor Compositiion in U.S. Manufacturing Industries: An Exploratory Analysis", Paper presented in honor of Zvi Griliches´sixtieth birthday, Jerusalem, May 1991, NBER Working Paper No. 4010.

[7] Binswanger, Hans P. (1974), "The Measurement of Technical Change Biases with Many Factors of Production," *American Economic Review*, 64(6), pp. 964-976.

[8] Boucekkine, R., F. Del Rio and O. Licandro (1999), "Endogenous vs Exogenously Driven Fluctuations in Vintage Capital Models", *Journal of Economic Theory*, 88(1), pp. 161-187

[9] Bresnahan, T., E. Brynjolfsson and L. Hitt (2002), "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm Level Evidence", *Quarterly Journal of Economics*, 117(1), February, pp. 339-376.

[10] Bureau of Economic Analysis, "National Income and Product Accounts", Survey of Current Business, July 1997.

[11] Caroli, E. and J. Van Reenen (2001), "Skill Biased Organizational Change? Evidence from a panel of British and French establishments", *Quarterly Journal of Economics*, 116(4), pp. 1449-1492.

[12] Chambers, R. G. (1988), "Applied Production Analysis: A Dual Approach", Cambridge University Press, Cambridge.

[13] Chennels, L. and J. Van Reenen (1999), "Has Technology Hurt Less Skilled Workers?", Institute for Fiscal Studies (IFS), Working Paper Series, W99/27.

[14] Christensen, L.R., D. W. Jorgenson and L .J. Lau (1973), "Transcendental Logarithmic Production Frontiers", *Review of Economics and Statistics*, 55, pp. 28-45.

[15] Chun, Hyunbae (2003), ” Information Technology and the Demand for Educated Workers: Disentangling the Impacts of Adoption Versus Use”, *Review of Economics and Statistics*, 85(1), pp. 1-8.

[16] Del Rio, Fernando (2001), ”Embodied technical progress and unemployment”, Université catholique de Louvain, Institut de Recherches Economiques et Sociales (IRES), discussion paper 2001031.

[17] Denison, Edward (1964), “The Unimportance of the Embodied Question”, *American Economic Review*, 54, pp. 90-93.

[18] Doms, Mark, Timothy Dunne and Kenneth Troske (1997), “Workers, Wages, and Technology”, *Quarterly Journal of Economics*, 112(1), pp. 253-90.

[19] Dunne, T., J. Haltiwagner and K.R. Troske (1996), “Technology and Jobs: Secular Changes and Cyclical Dynamics”, *Economic Studies* 96-7, US Cencus.

[20] Feenstra, R. C. and G. H. Hanson (1996), "Globalization, Outsourcing, and Wage Inequality," *American Economic Review*, 86(2), pp. 240-45.

[21] Fraumeni, B. M. (1997), “The Measurement of Depreciation in the U.S. National Income and Product Accounts”, Survey of Current Business, July.

[22] Goldin, C. and L. F. Katz (1996), “"Technology, Skill, and the Wage Structure: Insights from the Past”, *American Economic review*, 86(2), pp. 252-57.

[23] Gordon, Robert J. (1990), “The measurement of Durable Goods Prices”, University of Chicago Press.

[24] Gort, M. and R. A. Wall (1998, “Obsolescence, Input Augmentation, and Growth Accounting”, *European Economic Review*, 42(9), pp. 1653-65.

[25] Greenwood, J. and M. Yorukoglu (1997), “1974”, Carnegie-Rochester Conference Series on Public Policy, 46, pp. 49-95.

[26] Griliches, Zwi (1969), "Capital-Skill Complementarity." *Review of Economics and Statistics*, 51, pp. 465-468.

[27] Gunnarsson, G. and E. Mellander (1999), ”Input Aggregation Matters a Lot in Productivity Measurement, Even in the Short Run” presented at the 14th Annual Congress of the European Economic Association, Santiago de Compostela, Spain, 1999.

[28] Gunnarsson, G., E. Mellander and E. Savvidou (2001), “Is Human Capital the Key to the IT Productivity Paradox?”, IUI Working Paper nr 518.

[29] Hansson, P. (1996), “Technology and Changes in Employment of Skilled Labor in Swedish Manufacturing", FIEF Working Paper 131, Stockholm, Sweden.

[30] Haskel, J. and Y. Heden (1999), “Computers and Demand for Skilled Labour: Industry and Establishment Level Panel Evidence for the UK”, *The Economic Journal*, 109(454), March, pp. 68-79.

[31] Hobijn, Bart (2001), “Embodiment in U.S. Manufacturing”, mimeo, Federal Reserve Bank of New York, March 2001.

[32] Hornstein A. and P. Krusell (1996), “Can Technology Improvements Cause Productivity Slowdowns?“, NBER Macroeconomics Annual 11, MIT Press, pp.209-59.

[33] Kmenta, J. and R.F. Gilbert (1968), "Small sample properties of alternative estimators of seemingly unrelated regression", *Journal of the American Statistical Association*, 63, pp. 1180-1200.

[34] Krusell, Per, Lee E. Ohanian, José-Víctor Ríos-Rull and Giovanni L. Violante (2000), "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis", *Econometrica*, 68(5), September, pp. 1029-53.

[35] Lindquist, Matthew J. (2001), "Capital-Skill Complementarity and Inequality in Swedish Industry ", Department of Economics, Stockholm University Working Paper, 2002:14..

[36] Lindquist, Kjersti-Gro and Terje Skjerpen (2000), "Explaining the Change in Skill Structure of Labor Demand in Norwegian Manufacturing ", Discussion Paper 293 - Statistics Norway, December.

[37] Machin, S. and J. Van Reenen (1998), "Technology and Changes in Skill Structure: Evidence from Seven OECD Countries", *The Quarterly Journal of Econometrics*, 113(4), pp. 1215-1244.

[38] McHugh, Richard and Julia Lane (1983), "The Embodiment Hypothesis: an Interregional Test", *Review of Economics and Statistics*, 65, May, pp. 323-327.

[39] McHugh, Richard and Julia Lane (1987a), "The Role of Embodied Technical Change in the Decline of Labor Productivity", *Southern Economic Journal*, 53, pp. 915-924.

[40] McHugh, Richard and Julia Lane (1987b), " The Age of Capital, the Age of Utilized Capital, and Tests of the Embodiment Hypothesis", *Review of Economics and Statistics*, 69(2), May, pp. 362-367.

[41] Mellander, Erik (1999), "The Multi-Dimensional Nature of Labor Demand and Skill-Biased Technical Change", IFAU Working Paper 1999:9, Uppsala, Sweden.

[42] Morrison, C. J. (1997), "Assessing the Productivity of Information Technology Equipment in U.S. Manufacturing Industries", *Review of Economics and Statistics*, 79(3), pp. 471-481.

[43] Nelson, R. R. (1964), "Aggregate Production Functions and Medium-Range Growth Projections", *American Economic Review*, 54 (Sept.), 575-606.

[44] Oliner, Stephen D. (1994), "Measuring Stocks of Computer Peripheral Equipment: Theory and Applications", Board of Governors of the Federal Reserve System, May 1994.

[45] Oliner, Stephen D. and Daniel E. Sichel (1994), "Computers and Output Growth Revisited: How Big is the Puzzle?" Brookings Papers on Economic Activity 2, pp. 273-317.

[46] Phelps, E. (1962), "The New View of Investment: A Neoclassical Analysis", *Quarterly Journal of Economics*, 76, pp. 548-567.

[47] Sakellaris, Plutarchos and Daniel J. Wilson (2001), "Quantifying Embodied Technical Change", Federal Reserve Bank of San Francisco, Working Paper 2001-16 October.

[48] Solow, R. M. (1959), “Investment and Technical Progress”, in K. J. Arrow, S. Karlin and P. Suppes, eds., Mathemathical Methods in Social Sciences, (Stanford: University Press, 1960), pp. 89-104.

[49] Thompson, R. and T. G. Taylor (1995), “The Capital-Energy Substitutability Debate: A New Look”, *The Review of Economics and Statistics*, 77(3), pp. 565-69.

[50] Wood, Andrian (1994), “North-South Trade, Employment and Inequality: Changing Fortunes in a Skill-Driven World”, Oxford University Press, Oxford.

[51] You, Jong Keun (1976), “Embodied and Disembodied Technical Progress in the United States, 1929-1968”, *Review of Economics and Statistics*, 58, February, pp. 123-127.

[52] Zellner, Arnold (1962), “An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias”, *Journal of the American Statistical Association*, Volume 57, Issue 298, June.

APPENDIX:

A.1. Data description

The Swedish National Accounts (SNA) provides data on the industry level on capital stocks, labor and intermediate goods.

Data for two types of capital are provided by the SNA, namely equipment and structures. In order to obtain the IT capital stock, information provided in the yearly publications of the so-called *Investment Surveys* provided by Statistics Sweden have been used. These are aggregated over industries and provide information about computer investment for both office use and applications in production. For the estimation of the IT capital stock, the total gross investments of equipment, in current prices, is broken-down into computer and non-computer equipment. To compute IT investments in fixed prices, we have constructed an IT price index by means of Statistics Sweden data on imports of computers and peripherals, in current and fixed prices.

The disaggregation of labor into educational categories has been made possible by utilizing individual data from the Swedish Employment Register (SRE). This is an exhaustive register containing information by industry about workers, i.a. education, wage income and demographic characteristics. The labor data are adjusted for the incidence of part-time work by using industry-level information on the distribution on working hours by means of the Swedish Labour Force Survey (SLFS) provided in the SNA. In this way we obtain an approximation of the number of employees, provided by means of the SRE, into full-time equivalents. The approximation is due to the fact that the LFS does not contain data on work hours by level of education and thus only the part of the variation in the work hour distributions across levels of education that stems from differences in gender compositions, is captured.

The rental price for capital (K) is calculated according to the following equation:

$$P_{K,t} = P_{I,t-1}\left[r_{t-1} + d_K \frac{\left(P_{I,t/t-1}\right)^e}{P_{I,t-1}} - \left(\frac{\left(P_{I,t/t-1}\right)^e - P_{I,t-1}}{P_{I,t-1}}\right)\right]$$

where $P_{K,t}$ is the rental price at the beginning of period t, $P_{I,\, t-1,}$ is the gross investment price index for period t-1, r_{t-1} is a long-term interest rate measured at the very end of period t-1 and $(P_{I,\, t/t-1})^e$ is the expected value of the investment price index for period t, given information about this index up to (and including) period t-1.

The P_I and the δ_K are provided in the SNA. The interest rate is measured by means of the nominal rate on Swedish long-term industrial bonds and $(P_{I,\, t/t-1})^e$ is implemented by means of a univariate Kalman filter.

The capital rental price for computers is also calculated according to the equation above. For the gross investment price index, an import price index for computers, normalized to 1.0 in 1991, is used. Since this price index can only be computed for the period 1985-1995, the expected investment price index is calculated by means of a fitted linear trend to the log-differences of the computer import price index. This method is used instead of the Kalman filter used for the other types of capital.

For the construction of the price indexes for labor, we use information on payroll taxes for white-collar and blue-collar workers from *Näringslivets Ekonomifakta*, a private Swedish statistical agency. The price indexes for labor of category i, where i=1, 2, 3, 4, are given by the wage-bill for this category, including payroll taxes, divided by the labor input.

A.2.The extensive form of the stochastic version of the factor shares in equation (12) .

$$M_{X_{L_1}} = a_{L_1} + b_{L_1 t} TUIT + b_{L_1 L_1} \ell n X_{L_1} + b_{L_1 L_2} \ell n X_{L_2} + b_{L_1 L_3} \ell n X_{L_3} + b_{L_1 L_4} \ell n X_{L_4} + b_{L_1 C} \ell n X_C + b_{L_1 M} \ell n X_M + b_{L_1 S} \ell n X_S + b_{L_1 IG} \ell n X_{IG} + (b_{L_1 C}\, l_C)(t - G_t) + u_{L_1}$$

$$M_{X_{L_2}} = a_{L_2} + b_{L_2 t} TUIT + b_{L_2 L_1} \ell n X_{L_1} + b_{L_2 L_2} \ell n X_{L_2} + b_{L_2 L_3} \ell n X_{L_3} + b_{L_2 L_4} \ell n X_{L_4} + b_{L_2 C} \ell n X_C + b_{L_2 M} \ell n X_M + b_{L_2 S} \ell n X_S + b_{L_2 IG} \ell n X_{IG} + (b_{L_2 C}\, l_C)(t - G_t) + u_{L_2}$$

$$M_{X_{L_3}} = a_{L_3} + b_{L_3 t} TUIT + b_{L_3 L_1} \ell n X_{L_1} + b_{L_3 L_2} \ell n X_{L_2} + b_{L_3 L_3} \ell n X_{L_3} + b_{L_3 L_4} \ell n X_{L_4} + b_{L_3 C} \ell n X_C + b_{L_3 M} \ell n X_M + b_{L_3 S} \ell n X_S + b_{L_3 IG} \ell n X_{IG} + (b_{L_3 C}\, l_C)(t - G_t) + u_{L_3}$$

$$M_{X_{L_4}} = a_{L_4} + b_{L_4 t} TUIT + b_{L_4 L_1} \ell n X_{L_1} + b_{L_4 L_2} \ell n X_{L_2} + b_{L_4 L_3} \ell n X_{L_3} + b_{L_4 L_4} \ell n X_{L_4} + b_{L_4 C} X_C + b_{L_4 M} \ell n X_M + b_{L_4 S} \ell n X_S + b_{L_4 IG} \ell n X_{IG} + (b_{L_4 C}\, l_C)(t - G_t) + u_{L_4}$$

$$M_{X_C} = a_C + b_{Ct} TUIT + b_{CL_1} \ell n X_{L_1} + b_{CL_2} \ell n X_{L_2} + b_{CL_3} \ell n X_{L_3} + b_{CL_4} \ell n X_{L_4} + b_{CC} \ell n X_C + b_{CM} \ell n X_M + b_{CS} \ell n X_S + b_{CIG} \ell n X_{IG} + (b_{CC}\, l_C)(t - G_t) + u_C$$

$$M_{X_M} = a_M + b_{Mt} TUIT + b_{ML_1} \ell n X_{L_1} + b_{ML_2} \ell n X_{L_2} + b_{ML_3} \ell n X_{L_3} + b_{ML_4} \ell n X_{L_4} + b_{MC} \ell n X_C + b_{MM} \ell n X_M + b_{MS} \ell n X_S + b_{MIG} \ell n X_{IG} + (b_{MC}\, l_C)(t - G_t) + u_M$$

$$M_{X_S} = a_S + b_{St} TUIT + b_{SL_1} \ell n X_{L_1} + b_{SL_2} \ell n X_{L_2} + b_{SL_3} \ell n X_{L_3} + b_{SL_4} \ell n X_{L_4} + b_{SC} \ell n X_C + b_{SM} \ell n X_M + b_{SS} \ell n X_S + b_{SIG} \ell n X_{IG} + (b_{SC}\, l_C)(t - G_t) + u_S$$

$$M_{X_{IG}} = a_{IG} + b_{IGt} TUIT + b_{IGL_1} \ell n X_{L_1} + b_{IGL_2} \ell n X_{L_2} + b_{IGL_3} \ell n X_{L_3} + b_{IGL_4} \ell n X_{L_4} + b_{IGC} \ell n X_C + b_{IGM} \ell n X_M + b_{IGS} \ell n X_S + (b_{IGC}\, l_C)(t - G_t) + u_{IG}$$

A.3.The extensive form of the zero column sum restrictions in (13).

$$a_{L_1} + a_{L_2} + a_{L_3} + a_{L_4} + a_M + a_S + a_C + a_{IG} = 1$$

$$b_{L_1 t} + b_{L_2 t} + b_{L_3 t} + b_{L_4 t} + b_{Mt} + b_{St} + b_{Ct} + b_{IGt} = 0$$

$$b_{L_1 L_1} + b_{L_2 L_1} + b_{L_3 L_1} + b_{L_4 L_1} + b_{ML_1} + b_{SL_1} + b_{CL_1} + b_{IGL_1} = 0$$

$$b_{L_1 L_2} + b_{L_2 L_2} + b_{L_3 L_2} + b_{L_4 L_2} + b_{ML_2} + b_{SL_2} + b_{CL_2} + b_{IGL_2} = 0$$

$$b_{L_1 L_3} + b_{L_2 L_3} + b_{L_3 L_3} + b_{L_4 L_3} + b_{ML_3} + b_{SL_3} + b_{CL_3} + b_{IGL_3} = 0$$

$$b_{L_1 L_4} + b_{L_2 L_4} + b_{L_3 L_4} + b_{L_4 L_4} + b_{ML_4} + b_{SL_4} + b_{CL_4} + b_{IGL_4} = 0$$

$$b_{L_1C} + b_{L_2C} + b_{L_3C} + b_{L_4C} + b_{MC} + b_{SC} + b_{CC} + b_{IGC} = 0$$

$$b_{L_1M} + b_{L_2M} + b_{L_3M} + b_{L_4M} + b_{MM} + b_{SM} + b_{CM} + b_{IGM} = 0$$

$$b_{L_1S} + b_{L_2S} + b_{L_3S} + b_{L_4S} + b_{MS} + b_{SS} + b_{CS} + b_{IGS} = 0$$

$$b_{L_1IG} + b_{L_2IG} + b_{L_3IG} + b_{L_4IG} + b_{MIG} + b_{SIG} + b_{CIG} + b_{IGIG} = 0$$

$$b_{L_1t} + b_{L_2t} + b_{L_3t} + b_{L_4t} + b_{Mt} + b_{Ct} + b_{IGt} + b_{St} = 0$$

$$b_{L_1C}\, l_C + b_{L_2C}\, l_C + b_{L_3C}\, l_C + b_{L_4C}\, l_C + b_{MC}\, l_C + b_{SC}\, l_C + b_{CC}\, l_C + b_{IGC}\, l_C = 0$$

A.4. The extensive form of the restrictions

$$b_{L_1L_2} = b_{L_2L_1},\ b_{L_1L_3} = b_{L_3L_1},\ b_{L_1L_4} = b_{L_4L_1},\ b_{L_1C} = b_{CL_1},\ b_{L_1M} = b_{ML_1}$$

$$b_{L_1S} = -(b_{L_1L_1} + b_{L_2L_1} + b_{L_3L_1} + b_{L_4L_1} + b_{ML_1} + b_{CL_1} + b_{IGL_1})$$

$$b_{L_1IG} = b_{IGL_1}\ b_{L_2L_3} = b_{L_3L_2},\ b_{L_2L_4} = b_{L_4L_2},\ b_{L_2C} = b_{CL_2}\ b_{L_2M} = b_{ML_2}$$

$$b_{L_2S} = -(b_{L_1L_2} + b_{L_2L_2} + b_{L_3L_2} + b_{L_4L_2} + b_{ML_2} + b_{CL_2} + b_{IGL_2})$$

$$b_{L_2IG} = b_{IGL_2},\ b_{L_3L_4} = b_{L_4L_3},\ b_{L_3C} = b_{CL_3},\ b_{L_3M} = b_{ML_3}$$

$$b_{L_3S} = -(b_{L_1L_3} + b_{L_2L_3} + b_{L_3L_3} + b_{L_4L_3} + b_{ML_3} + b_{CL_3} + b_{IGL_3})$$

$$b_{L_3IG} = b_{IGL_3},\ b_{L_4C} = b_{CL_4},\ b_{L_4M} = b_{ML_4},\ b_{L_4IG} = b_{IGL_4}$$

$$b_{L_4S} = -(b_{L_1L_4} + b_{L_2L_4} + b_{L_3L_4} + b_{L_4L_4} + b_{ML_4} + b_{CL_4} + b_{IGL_4})$$

$$b_{CM} = b_{MC},\ b_{CS} = -(b_{L_1C} + b_{L_2C} + b_{L_3C} + b_{L_4C} + b_{MC} + b_{CC} + b_{IGC})$$

$$b_{CIG} = b_{IGC},\ b_{MS} = -(b_{L_1M} + b_{L_2M} + b_{L_3M} + b_{L_4M} + b_{MM} + b_{CM} + b_{IGM})$$

$$b_{SS} = -(b_{SL_1} + b_{SL_2} + b_{SL_3} + b_{SL_4} + b_{SM} + b_{SC} + b_{SIG}),\ b_{MIG} = b_{IGM}$$

$$b_{IGS} = -(b_{L_1IG} + b_{L_2IG} + b_{L_3IG} + b_{L_4IG} + b_{MIG} + b_{CIG} + b_{IGIG})$$

A.5. The extensive form of equation (15)

$$M_{X_{L_1}} = a_{L_1} + b_{L_1t}TUIT + b_{L_1L_1}\ell n\left(\frac{X_{L_1}}{X_S}\right) + b_{L_1L_2}\ell n\left(\frac{X_{L_2}}{X_S}\right) + b_{L_1L_3}\ell n\left(\frac{X_{L_3}}{X_S}\right) + b_{L_1L_4}\ell n\left(\frac{X_{L_4}}{X_S}\right) +$$
$$b_{L_1M}\ell n\left(\frac{X_M}{X_S}\right) + b_{L_1C}\ell n\left(\frac{X_C}{X_S}\right) + b_{L_1IG}\ell n\left(\frac{X_{IG}}{X_S}\right) + (b_{L_1C}\, l_C)(t - G_t) + u_{L_1}$$

$$M_{X_{L_2}} = a_{L_2} + b_{L_2t}TUIT + b_{L_2L_1}\ell n\left(\frac{X_{L_1}}{X_S}\right) + b_{L_2L_2}\ell n\left(\frac{X_{L_2}}{X_S}\right) + b_{L_2L_3}\ell n\left(\frac{X_{L_3}}{X_S}\right) + b_{L_2L_4}\ell n\left(\frac{X_{L_4}}{X_S}\right) +$$
$$b_{L_2M}\ell n\left(\frac{X_M}{X_S}\right) + b_{L_2C}\ell n\left(\frac{X_C}{X_S}\right) + b_{L_2IG}\ell n\left(\frac{X_{IG}}{X_S}\right) + (b_{L_2C}\, l_C)(t - G_t) + u_{L_2}$$

$$M_{X_{L_3}} = a_{L_3} + b_{L_3t}TUIT + b_{L_3L_1}\ell n\left(\frac{X_{L_1}}{X_S}\right) + b_{L_3L_2}\ell n\left(\frac{X_{L_2}}{X_S}\right) + b_{L_3L_3}\ell n\left(\frac{X_{L_3}}{X_S}\right) + b_{L_3L_4}\ell n\left(\frac{X_{L_4}}{X_S}\right) +$$
$$b_{L_3M}\ell n\left(\frac{X_M}{X_S}\right) + b_{L_3C}\ell n\left(\frac{X_C}{X_S}\right) + b_{L_3IG}\ell n\left(\frac{X_{IG}}{X_S}\right) + (b_{L_3C}\, l_C)(t - G_t) + u_{L_3}$$

$$M_{X_{L_4}} = a_{L_4} + b_{L_4t}TUIT + b_{L_4L_1}\ell n\left(\frac{X_{L_1}}{X_S}\right) + b_{L_4L_2}\ell n\left(\frac{X_{L_2}}{X_S}\right) + b_{L_4L_3}\ell n\left(\frac{X_{L_3}}{X_S}\right) + b_{L_4L_4}\ell n\left(\frac{X_{L_4}}{X_S}\right) +$$
$$b_{L_4M}\ell n\left(\frac{X_M}{X_S}\right) + b_{L_4C}\ell n\left(\frac{X_C}{X_S}\right) + b_{L_4IG}\ell n\left(\frac{X_{IG}}{X_S}\right) + (b_{L_4C}\, l_C)(t - G_t) + u_{L_4}$$

$$M_{X_C} = a_C + b_{Ct}TUIT + b_{CL_1}\ell n\left(\frac{X_{L_1}}{X_S}\right) + b_{CL_2}\ell n\left(\frac{X_{L_2}}{X_S}\right) + b_{CL_3}\ell n\left(\frac{X_{L_3}}{X_S}\right) + b_{CL_4}\ell n\left(\frac{X_{L_4}}{X_S}\right) +$$
$$b_{CM}\ell n\left(\frac{X_M}{X_S}\right) + b_{CC}\ell n\left(\frac{X_C}{X_S}\right) + b_{CIG}\ell n\left(\frac{X_{IG}}{X_S}\right) + (b_{CC}\, l_C)(t - G_t) + u_C$$

$$M_{X_M} = a_M + b_{Mt}TUIT + b_{ML_1}\ell n\left(\frac{X_{L_1}}{X_S}\right) + b_{ML_2}\ell n\left(\frac{X_{L_2}}{X_S}\right) + b_{ML_3}\ell n\left(\frac{X_{L_3}}{X_S}\right) + b_{ML_4}\ell n\left(\frac{X_{L_4}}{X_S}\right) +$$
$$b_{MM}\ell n\left(\frac{X_M}{X_S}\right) + b_{MC}\ell n\left(\frac{X_C}{X_S}\right) + b_{MIG}\ell n\left(\frac{X_{IG}}{X_S}\right) + (b_{MC}\, l_C)(t - G_t) + u_M$$

$$M_{X_{IG}} = a_{IG} + b_{IGt}TUIT + b_{IGL_1}\ell n\left(\frac{X_{L_1}}{X_S}\right) + b_{IGL_2}\ell n\left(\frac{X_{L_2}}{X_S}\right) + b_{IGL_3}\ell n\left(\frac{X_{L_3}}{X_S}\right) + b_{IGL_4}\ell n\left(\frac{X_{L_4}}{X_S}\right) +$$
$$b_{IGM}\ell n\left(\frac{X_M}{X_S}\right) + b_{IGC}\ell n\left(\frac{X_C}{X_S}\right) + b_{IGIG}\ell n\left(\frac{X_{IG}}{X_S}\right) + (b_{IGC}\, l_C)(t - G_t) + u_{IG}$$

A.5.Table 8: Continuation of table 1- the rest of the estimated parameters.

	Regression I	Regression II	Regression III
$b_{L_1L_1}$	0.050516***	0.062395***	0.053939***
$b_{L_1L_2}$	-0.02004***	-0.01329***	-0.01728***
$b_{L_1L_3}$	-0.02301***	-0.03071***	-0.0221***
$b_{L_1L_4}$	-0.01437***	-0.02169***	-0.01883***
b_{L_1M}	0.010405***	-0.00023	0.005741**
b_{L_1C}	0.003394***	0.006064***	0.004614***
b_{L_1IG}	0.005264	-0.00401	0.003781
$b_{L_2L_2}$	0.045634***	0.044825***	0.045782***
$b_{L_2L_3}$	-0.01055***	-0.01189***	-0.01133***
$b_{L_2L_4}$	-0.00084	-0.00482**	-0.00242
b_{L_2M}	0.001572	-0.00022	0.001071
b_{L_2C}	0.00034	0.002269***	0.001843***
b_{L_2IG}	-0.01925***	0.02265***	-0.01971***
$b_{L_3L_3}$	0.142825***	0.147999***	0.14177***
$b_{L_3L_4}$	-0.01027*	-0.01211**	-0.01194**
b_{L_3M}	-0.01467***	-0.01029***	-0.01296***
b_{L_3C}	-0.0009	0.001068	0.000948
b_{L_3IG}	-0.10286***	-0.09916***	-0.10193***
$b_{L_4L_4}$	0.064618***	0.071889***	0.068454***
b_{L_4M}	0.009447***	0.016248***	0.011877***
b_{L_4C}	-0.00254**	-0.00534***	-0.00459***
b_{L_4IG}	-0.03555***	-0.02827***	-0.03331***
b_{MM}	0.024595***	0.018895***	0.025717***
b_{MIG}	-0.03505***	-0.02992***	-0.03529***
b_{MC}	-0.00338***	-0.00232***	-0.00403***
b_{IGIG}	0.215033***	0.223172***	0.213377***
b_{IGC}	-0.00641***	-0.00792***	-0.00648***